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Queue-based power control in UMTS systems

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***Abstract*— In modern cellular communication systems, power control plays a fundamental role for efficient resource utilization. In such systems, in fact, many users transmit over the same radio channel using the same frequency band and time slots so that the signal of an individual user becomes interference for the other users. Hence the transmission power levels need to be smartly manipulated so as to achieve an adequate *quality of service* for as many users as possible and, thus, an efficient network utilization. Conventional power control algorithms adopt the *Signal-to-Interference-plus-Noise Ratio (SINR)* as controlled variable and neglect the important effects of the manipulated control variables (transmission powers) and of the retransmission mechanism on the queueing dynamics. In this paper, we pursue a different *queue-based* approach which takes into account the queuing dynamics and adopts the *queue size* as controlled variable. In particular, a novel *queue-based* power control algorithm with low on-line computational burden is proposed and its performance is evaluated both theoretically and via simulation experiments.**

I. INTRODUCTION

Power control [1] is a key issue for the efficient management of cellular communication networks as it attempts to mantain a satisfactory *Quality of Service (QoS)* for as many users as possible. In this paper, the focus will be on the uplink communication in a *Wideband Code Division Multiple Access (WCDMA)* system.

There are essentially two methods by which power control can be performed, i.e.

- **Centralized Power Control - CPC** in which the *base station* commands, according to the available measurements, the *mobile stations* to adjust their transmission powers; or
- **Distributed Power Control - DPC** in which the *base station* sends a metric describing the link quality, according to which the *mobile stations* decide their transmission powers.

In CPC [2]-[3], the base station can take into account the situations of multiple mobile stations when making a decision. However, CPC involves added infrastructure and introduces a feedback delay in the power control process, which degrades the system performance. For these reasons, CPC is inpractical and several DPC schemes have been proposed [4]-[10]. In all the power control algorithms so far presented in the literature - see e.g. the survey papers [7] and [11] - the primary control objective is expressed by the requirement that the SINR of each user does not exceed a pre-specified threshold determined by QoS specifications. In contrast to the conventional *SINR-based* approach, a novel *queue-based* approach will be pursued in the present paper. The idea of this approach is to express the QoS of each user in terms of its queue size (i.e. the number of packets waiting to be transmitted by the user) instead of SINR. To this end, the effect of the transmission power on the queue dynamics is modeled and power control can be cast into an optimal control problem with a criterion trading-off the conflicting issues of high performance (low queues) and low costs (low transmission powers). In particular, a computationally efficient *Queue-Based Distributed Power Control (QBDPC)* algorithm is proposed. The performance of QBDPC has been analyzed theoretically and has been compared, via simulation experiments, with the performance of other SINR-based DPC algorithms having a similar on-line computational burden, showing that the queue-based approach is indeed promising. The rest of the paper is organized as follows. Section II describes the uplink power control problem for a WCDMA system. Section III introduces the queue-based approach to power control and the QBDPC algorithm. Section IV and V provide steady-state analysis and, respectively, convergence analysis of the QBDPC-controlled network. Section VI presents simulation results and, finally, section VII ends the paper.

II. POWER CONTROL IN UMTS NETWORKS

Let us consider a single-cell WCDMA system with M *Mobile Stations* MS_i, $i = 1, 2, \ldots, M$, sharing the same channel to the *Base Station* (BS). Let g_i denote the channel gain between MS_i and BS and u_i the transmission power from MS_i to BS. Then the achieved *Signal to Interference plus Noise Ratio (SINR)* for MS_i can be expressed as

$$\gamma_i \;=\; \frac{L g_i \; u_i}{\sigma^2 + \sum_{j \neq i} g_j u_j} \qquad (1)$$

where $\sigma^2 > 0$ is the noise power at the BS and $L > 1$ is the *spreading gain* (chip rate to bit rate ratio) of the WCDMA system. The power control algorithms actually in use in WCDMA systems, as well as the ones so far proposed in the literature, adopt the SINR as controlled variable, i.e. adjust the transmission power u_i so as to regulate the SINR γ_i at a pre-specifed setpoint related to the desired QoS of user MS_i. These algorithms will be referred to in this paper as *SINR-based* power control algorithms. For QoS management, however, it seems more appropriate to control the queue size

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in each MS rather than the SINR. In fact, the QoS perceived by each user is expressed in terms of the service delay and of the packet loss rate which, in turn, are directly related to the size of the user's queue, i.e. the number of packets waiting to be transmitted by the user. Hence, it might be advisable to either reduce or increase the transmission power depending on the current queue state rather than on the current SINR.

For this reason a different *queue-based* approach to distributed power control will be described in the next section.

III. QUEUE-BASED POWER CONTROL

Each user MS_i is modelled as a queue with state equation

$$x_i(t+1) = x_i(t) + w_i(t) - v_i(t) \tag{2}$$

where $x_i(t), w_i(t), v_i(t)$ denote respectively the queue size, input flow, output flow (measured in packets) at sample time t. In turn, the output flow $v_i(t)$ is modeled by

$$v_i(t) = R\,(1 - PER_i(t)) \tag{3}$$

where R is the fixed channel transmission capacity (packets transmitted per sampling period) and $PER_i(t)$ is the *packet error rate* of MS_i at sample time t. Finally it is assumed that the PER is a known decreasing function of the SINR, i.e.

$$PER_i(t) \;=\; G\,(\gamma_i(t))\,. \tag{4}$$

Notice that, combining (3) and (4), the output flow is related to the SINR by

$$v_i(t) \;=\; F\,(\gamma_i(t)) = F_i\,(u(t)) \tag{5}$$

where: $F(\gamma) \triangleq R\,(1 - G(\gamma))$ is an increasing function of γ; $u = [u_1, u_2, \ldots, u_M]$ is the vector of all transmission powers and $F_i(u) \triangleq F\left(\left(\sigma^2 + \sum_{j\neq i} g_j u_j\right)^{-1} L g_i u_i\right)$. In a centralized power control scheme, the objective would be to choose, at each sampling time t, the whole control vector $u(t)$ based on the knowledge of the whole state vector $x(t) = [x_1(t), x_2(t), \ldots, x_M(t)]$ so as to possibly optimize some global network utility. In particular, a predictive control approach could be pursued by defining a suitable finite-horizon cost $J(x(t); u(t), u(t+1), \ldots, u(t+H-1))$ which trades off QoS (low queue sizes) vs. battery usage (low powers), and by designing the power control $u(t)$, at time t, as the first element of the optimal control sequence minimizing such a cost according to the so called *receding-horizon* strategy. However, centralized power control is not viable in practice and a decentralized (distributed) control scheme, wherein each user MS_i selects its own transmission power u_i based on local information only, must be adopted. In this context it is assumed that user MS_i, besides the knowledge of the local state x_i and input flow w_i, has also measurements (or estimates) of the gain g_i and of the total interference-plus-noise power at the BS (denominator of the SINR)

$$\sigma_i^2 = \sigma^2 + \sum_{j\neq i} g_j u_j \tag{6}$$

It is further assumed that such quantities $g_i(t)$ and $\sigma_i^2(t)$ are slowly varying with time t and that, for the purpose of control design, the available estimates are exact. Exploiting (1), (5) and (6), the transmission power $u_i(t)$ turns out to be related to the output flow $v_i(t)$ by

$$u_i(t) \;=\; \frac{\sigma_i^2(t)}{L g_i(t)}\; F^{-1}\,(v_i(t)) \tag{7}$$

The goal of distributed power control is, therefore, to design a power control law $u_i = u_i(x_i, w_i, g_i, \sigma_i^2)$ in each mobile station MS_i so as to optimize a local performance index. To this end, the following cost is introduced for MS_i

$$J_i(x_i(t), u_i(t)) \;=\; x_i^2(t+1) + r_i v_i^2(t) \tag{8}$$

where $r_i > 0$. Notice that in (8) a control horizon $H = 1$ has been chosen and a quadratic penalization v_i^2, instead of u_i^2, has been considered to avoid nonlinearity of (2) w.r.t. u_i. It will be seen hereafter that these choices greatly simplify the underlying optimal control problem and also provide a resulting control law with low on-line computational burden. The *Queue-Based Distributed Power Control (QBDPC)* problem is therefore formulated as follows:

$$\begin{array}{l} \text{for } i = 1, 2, \ldots, M : \\ u_i(t) = \arg\min\limits_{u_i(t)} \; x_i^2(t+1) + r_i v_i^2(t) \end{array} \tag{9}$$

subject to

$$\left\{ \begin{array}{rcl} x_i(t+1) & = & x_i(t) + w_i(t) - v_i(t) \\ v_i(t) & = & F\left(\frac{L g_i(t)}{\sigma_i^2(t)} u_i(t)\right) \\ \underline{u} & \leq & u_i(t) \leq \overline{u} \end{array} \right. \tag{10}$$

where $\underline{u}$ and $\overline{u}$ represent the lower and, respectively, upper limitation on the transmission power of a MS.

Theorem 1: - The solution to the above QBDPC problem (9)-(10) is given by the following QBDPC control law

$$\begin{array}{rcl} \text{For } i & = & 1, 2, \ldots, M \\ v_i^*(t) & = & \frac{1}{1+r_i}\,(x_i(t) + w_i(t)) \\ \gamma_i^*(t) & = & F^{-1}\,(v_i^*(t)) \\ u_i^*(t) & = & \frac{\sigma_i^2(t)}{L g_i(t)}\;\gamma_i^*(t) \\ u_i(t) & = & sat\,(u_i^*(t)) \end{array} \tag{11}$$

where

$$sat(u) \triangleq \left\{ \begin{array}{ll} \underline{u}, & u < \underline{u} \\ u, & \underline{u} \leq u \leq \overline{u} \\ \overline{u}, & u > \overline{u} \end{array} \right.$$

Proof: see [12]. ■

Please notice that the proposed QBDPC control law involves only few algebraic calculations and is therefore amenable to fast on-line implementation in a WCDMA system, without requiring excessive processing capabilities to the mobile stations. Performance can be tuned by each mobile station MS_i by properly selecting, possibly in a time-varying fashion, the parameter $r_i > 0$. A possible way is to choose r_i based on some measured indicator of QoS, so that r_i is taken larger (smaller) whenever the measured QoS is higher (lower). Performance issues will be investigated in the last section by means of simulation experiments.

IV. STEADY-STATE ANALYSIS

Let us assume, for the purposes of analysis, that the gains g_i, the flows w_i and the noise power at the BS σ^2 are constant. The goal is to find if there exists a corresponding equilibrium. For ease of notation, the equilibrium values will be simply denoted by $v_i, PER_i, \gamma_i, x_i, u_i$ not to be confused with the time-varying $v_i(t), PER_i(t), \gamma_i(t), x_i(t), u_i(t)$ considered so far. Further, let us assume (this assumption will be discussed later) that the equilibrium values are such that the power saturation constraints are not violated. Hence from (2)-(5) and (11) it is easy to see that

$$\begin{array}{l} v_i = w_i, \ x_i = r_i w_i, \ PER_i = 1 - \dfrac{w_i}{R}, \\ \gamma_i = G^{-1}\left(1 - \frac{w_i}{R}\right) = F^{-1}(w_i) \end{array} \tag{12}$$

are the equilibrium output flows, queue sizes, PERs and SINRs related to the constant input flows w_i. Given the above equilibrium SINRs γ_i, the corresponding equilibrium transmission powers u_i can be found via (1). For notational convenience, let us denote the i-th user's power received at the BS as $\tilde{u}_i \stackrel{\triangle}{=} g_i u_i$. Then (1) implies the following linear equations

$$\frac{L}{\gamma_i}\ \tilde{u}_i - \sum_{j \neq i} \tilde{u}_j \ = \ \sigma^2 \qquad i = 1, 2, \ldots, M \tag{13}$$

to be solved w.r.t. the unknown $\tilde{u}_i$. Subtracting the i-th and j-th equations in (13), for any $j \neq i$, one gets

$$\left(\frac{L}{\gamma_i} + 1\right) \tilde{u}_i - \left(\frac{L}{\gamma_j} + 1\right) \tilde{u}_j = 0 \ \Rightarrow \ \tilde{u}_j = \frac{\gamma_j (L + \gamma_i)}{\gamma_i (L + \gamma_j)}\ \tilde{u}_i. \tag{14}$$

Substitution of (14) into (13) yields the solution

$$u_i \ = \ \frac{\tilde{u}_i}{g_i} \ = \ \frac{\sigma^2 \gamma_i / g_i}{L - (L + \gamma_i)\ \sum_{j \neq i} \dfrac{\gamma_j}{L + \gamma_j}} \tag{15}$$

Clearly, for feasibility it must be $u_i \geq 0$ for all i. Notice from (14) that all non-zero powers must have the same sign and hence the unique condition required for positivity is

$$\frac{L}{L + \gamma_i} \ > \ \sum_{j \neq i} \frac{\gamma_j}{L + \gamma_j} \tag{16}$$

Notice that any value of i can be considered in (16) since from the above analysis it turns out that validity of (16) for some i implies validity for all i. It is easy to see that the left-hand-side of (16) is decreasing (from 1 to 0) in γ_i while the right-hand-side is increasing (from 0 to 1) in γ_j. This implies that (16) always holds for sufficiently small γ_i i.e., since $w_i = F(\gamma_i)$ and $F(\cdot)$ is monotonic increasing, for sufficiently small flows w_i. This suggests that if (16) is not satisfied, one can decrease some (or all) users' flow rates. There can be clearly several strategies in order to ensure feasibility, e.g. to reduce all users' flows w_i of the same factor, or to reduce the various flows by different amounts by some QoS agreement between the BS and the users, or simply to drop some users by some *admission control* scheme.

Since the power levels must satisfy physical limitations $\underline{u} \leq u_i \leq \overline{u}$, feasibility requires the conditions:

$$\underline{u} \leq \frac{\sigma^2 \gamma_i / g_i}{L - (L + \gamma_i)\ \sum_{j \neq i} \dfrac{\gamma_j}{L + \gamma_j}} \leq \overline{u} \qquad i = 1, 2, \ldots, M \tag{17}$$

Hereafter it will be assumed that the equilibrium defined by (12) and (15) satisfy the feasibility conditions (17) which, in turn, ensures that the equilibrium does not violate the power limitations.

V. CONVERGENCE

From a theoretical point of view, it is important to establish stability of the proposed QBDPC algorithm, i.e. convergence, under steady-state flows and gains, to the equilibrium analyzed in the previous section. The following result holds.

Theorem 2: Consider the power system (1)-(5), with constant input flows w_i and gains g_i, subject to the QBDPC algorithm (11). Let the input flows w_i, for $i = 1, 2, \ldots, M$, satisfy the following conditions

$$F\left(\frac{L g_i \underline{u}}{\sigma^2 + (M-1)\underline{u}}\right) < w_i < F\left(\frac{L g_i \overline{u}}{\sigma^2 + (M-1)\overline{u}}\right) \tag{18}$$

Then the system converges to the equilibrium defined by (12) and (15).

Proof - Notice that from (18)

$$F\left(\frac{L g_i \underline{u}}{\sigma^2 + \sum_{j \neq i} g_j u_j}\right) < w_i < F\left(\frac{L g_i \overline{u}}{\sigma^2 + \sum_{j \neq i} g_j u_j}\right) \tag{19}$$

for any u_j, $j = 1, 2, \ldots, M$, such that $\underline{u} \leq u_j \leq \overline{u}$. This, in turn, implies feasibility of the equilibrium (15) i.e. $\underline{u} \leq u_i \leq \overline{u}$. We first prove that the size of the MS_i's queue converges to $x_i = r_i w_i$. In fact $x_i(t)$ obeys the state equation (2) where, under the QBDPC law,

$$v_i(t) = \max\left\{\min\left[v_i^*(t), F\left(\frac{L g_i \overline{u}}{\sigma_i^2(t)}\right)\right], F\left(\frac{L g_i \underline{u}}{\sigma_i^2(t)}\right)\right\}$$

and $v_i^*(t)$ is defined in (11). Now, if $x_i(t) > r_i w_i$, $v_i^*(t) > w_i$ from which $v_i(t) > w_i$ and, by (2), $x_i(t)$ decreases. Conversely, if $x_i(t) < r_i w_i$, $v_i^*(t) < w_i$ from which $v_i(t) <$

w_i and, by (2), $x_i(t)$ increases. Thus $\lim_{t\to\infty} x_i(t) = x_i = r_i w_i$ for any $x_i(0)$ and, consequently, $\lim_{t\to\infty} v_i(t) = w_i$ and $\lim_{t\to\infty} \gamma_i^*(t) = \gamma_i = F^{-1}(w_i)$ where $\gamma_i^*(t)$ is defined in (11). Let us now prove that for $t \to \infty$ $u_i(t)$ tend to the equilibrium values given by (15). First notice that

$$\begin{array}{rcccl} \tilde{u}_i^*(t) & \stackrel{\triangle}{=} & g_i u_i^*(t) & = & \dfrac{\sigma^2 + \sum_{j\neq i} \tilde{u}_j(t-1)}{L}\gamma_i^*(t) \\ \tilde{u}_i & \stackrel{\triangle}{=} & g_i u_i & = & \dfrac{\sigma^2 + \sum_{j\neq i} \tilde{u}_j}{L}\gamma_i \end{array} \quad (20)$$

Due to feasibility of the equilibrium, $u_i \in [\underline{u}, \overline{u}]$. Then for sufficiently large t, since $\gamma_i^*(t) \to \gamma_i$ for $t \to \infty$ and by virtue of (19), also $u_i^*(t) \in [\underline{u}, \overline{u}]$. Let us define $\delta\tilde{u}_i(t) \stackrel{\triangle}{=} \tilde{u}_i(t) - \tilde{u}_i$. For sufficiently large t, $u_i(t) = sat(u_i^*(t)) = u_i^*(t)$ and hence

$$\delta\tilde{u}_i(t) = \frac{\gamma_i}{L}\sum_{j\neq i}\delta\tilde{u}_j(t-1) + \frac{\sigma^2 + \sum_{j\neq i}\tilde{u}_j(t-1)}{L}\left(\gamma_i^*(t) - \gamma_i\right)$$

Then

$$|\delta\tilde{u}_i(t)| \leq \frac{\gamma_i}{L}\sum_{j\neq i}|\delta\tilde{u}_j(t-1)| + \frac{\sigma^2 + (M-1)\overline{u}}{L}|\gamma_i^*(t) - \gamma_i|$$

Defining the vector $\delta\tilde{u}(t) \stackrel{\triangle}{=} [\delta\tilde{u}_1(t), \delta\tilde{u}_2(t), \ldots, \delta\tilde{u}_M(t)]'$:

$$\|\delta\tilde{u}(t)\|_\infty \leq a\ \|\delta\tilde{u}(t-1)\|_\infty\ +\ b\ \left[\ \sup_i |\gamma_i^*(t) - \gamma_i|\ \right] \quad (21)$$

where

$$a \stackrel{\triangle}{=} \frac{M-1}{L}\sup_i\ \gamma_i, \quad b \stackrel{\triangle}{=} \frac{\sigma^2 + (M-1)\overline{u}}{L}$$

Notice that from (18):

$$\gamma_i = F^{-1}(w_i) < \frac{L}{M-1} \implies 0 < a < 1$$

Hence (21) shows that $\|\delta\tilde{u}(t)\|_\infty$ is bounded from above by the response of an asymptotically stable (first-order) system $\xi(t+1) = a\xi(t) + b\omega(t)$ with an input $\omega(t) \stackrel{\triangle}{=} \sup_i |\gamma_i^*(t) - \gamma_i|$ converging to zero. Since such a response $\xi(t)$ is converging to zero, $\delta\tilde{u}(t) \to 0$ for $t \to \infty$ and, hence, $\lim_{t\to\infty} u_i(t) = u_i$ for $i = 1, 2, \ldots, M$. ∎

VI. SIMULATIONS

The QBDPC algorithm described in the previous section is compared with the following two SINR-based algorithms:

- the *Up/Down Centralized Power Control* algorithm which has been standardized by 3GPP (1999) to be used in WCDMA;
- the DPC algorithm of Alpcan *et al.* (2002) which is based on *game theory* and will be referred to hereafter as *Game-Theoretic DPC (GTDPC)*.

The UDCPC algorithm is run at the BS and assumes centralized information on all $\gamma_i(t)$ for $i = 1, 2, \ldots, M$. More precisely, UDCPC operates as follows

$$[u_i(t)]_{dB} = [u_i(t-1)]_{dB} + sign\left(\gamma_i^* - \gamma_i(t)\right)\ \delta u \quad (22)$$

where δu is a fixed *power step* (in decibel) while γ_i^* and $\gamma_i(t)$ are the *target* and, respectively, *estimated SINR* of MS_i. This power update (fixed step increase/decrease) is typically performed at a rate of $1.5\ KHz$.

The GTDPC algorithm is, conversely, a distributed algorithm run in each MS_i. It is based on minimization in each MS_i of a local cost function

$$J_i(u_i, \gamma_i)\ =\ \alpha_i u_i - \beta_i\ log(1 + \gamma_i)$$

where the first represents a penalty proportional to the used transmission power and the second term an utility proportional to the channel capacity. The resulting GTDPC control law is given by

$$u_i(t) = \max\left(0, \frac{\beta_i}{\alpha_i} - \frac{\sigma_i^2(t)}{Lg_i(t)}\right). \quad (23)$$

In order to comparatively evaluate the performance of the QBDPC, UDCPC and GTDPC algorithms, a WCDMA communication system has been simulated. The simulations have been run under the following hypotheses:

- single cell controlled by one base station (BS);
- up link;
- mobile stations (MS) have different distances to the BS (near-far);
- each user (MS) has an asynchronous packet traffic flow to the BS with ARQ Stop and Wait protocol;
- each MS can have two different types of traffic: voice and data (details in table I);
- the background noise power is fixed at 10dB lower than the signal;
- perfect SINR estimation is supposed;
- the PER target for the voice service is 10%, while data has 0.1%;
- the relation between the PER and the SINR (4) for coded transmissions can be extracted from [13].

A multipath fading channel has been modeled [3]. The channel has 4 taps whose amplitudes and phases are Rayleigh and uniform distributed, respectively. Moreover, two possible user *mobilities* (Doppler frequency, f_d) have been considered: *pedestrian* ($f_d = 3Hz$) and *vehicular* ($f_d = 120Hz$).

TABLE I

TYPES OF TRAFFIC FLOW PER USER.

Type of traffic	Rate	L	Coding
Voice	60 kbps	64	1/2 convolutional
Data (interactive)	480 kbps	8	1/3 turbocode

TABLE II

SIMULATION PARAMETERS.

Minimum time unit	10^{-7}sec
Packet time	0.667 msec
Acknowledge time of one packet	10^{-5}sec
Multipath fading variance (rural)	-3.6dB
Multipath fading variance (urban)	-5.7dB
Start up MS transmission power	10mW
Minimum transmission power	1mW
Maximum transmission power (voice)	125 mW
Maximum transmission power (data)	250 mW
Frequency of QBDPC	200Hz
Frequency of UDCPC	1500Hz
Frequency of GTDPC	200Hz
Parameter r_i of QBDPC	$log_2(1+\gamma_i)$

The following simulation experiment, of duration equal to $6500\ s$, has beeen performed: a first group of 4 users (mobile stations) is initially present in the cell; then a second group of 3 users enters the cell at time $t_1 = 2500\ s$; next, the users of the first group leave the cell at time $t_2 = 4500\ s$. All the simulation parameters are reported in table II.

In figs. 1 and 2 the behavior of the number of queued packets for the three algorithms is shown. It can be seen that UDCPC, QBDPC and GTDPC have comparable queue sizes. On the other hand, if the comparison is switched to the average transmission power (see figs. 3 and 4), it can be noticed that the QBDPC reaches the same queue sizes with lower transmission powers compared to the GTDPC and UDCPC algorithms. Fig. 5 displays the time evolution of the transmission power for each user in the system. Again, the proposed algorithm outperforms other schemes even instantaneously. Finally, from fig. 6 it is possible to appreciate that, for a given SINR, the QBDPC algorithm is able to efficiently save power compared to GTDPC and even more to UDCPC as well as assuring small queues in the system compared to GTDPC and even more to UDCPC. These conclusions can be drawn by looking at the voice or data information sources, indifferently.

VII. CONCLUSIONS

The paper has addressed power control in wireless WCDMA communication networks with a novel, *queue-based*, approach. This approach relies on modelling how the transmission powers affect the queueing dynamics and

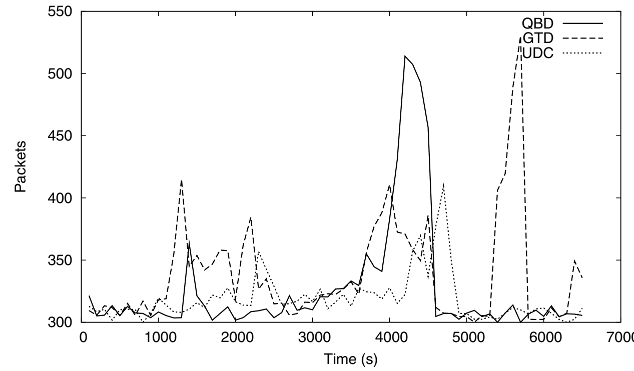

Fig. 1. Voice queue sizes for QBDPC, GTDPC and UDCPC.

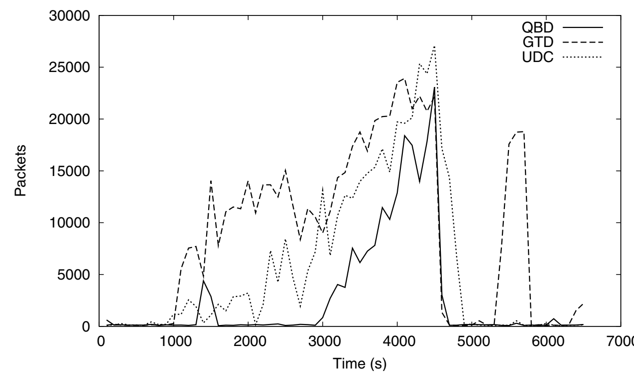

Fig. 2. Data queue sizes for QBDPC, GTDPC and UDCPC.

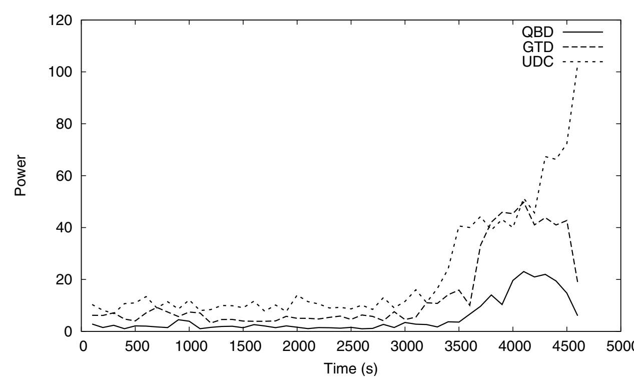

Fig. 3. Average transmission powers for the voice packets of QBDPC, GTDPC and UDCPC.

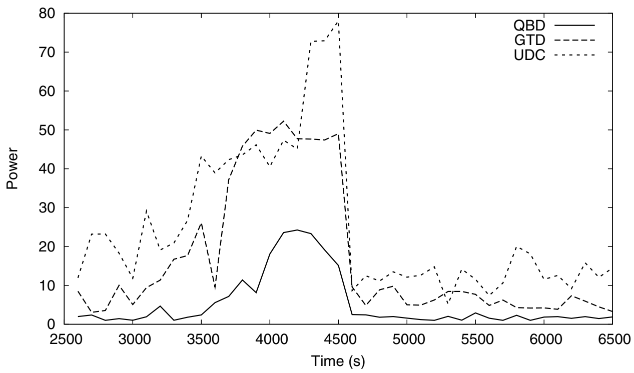

Fig. 4. Average transmission powers for the data packets of the QBDPC, GTDPC and UDCPC.

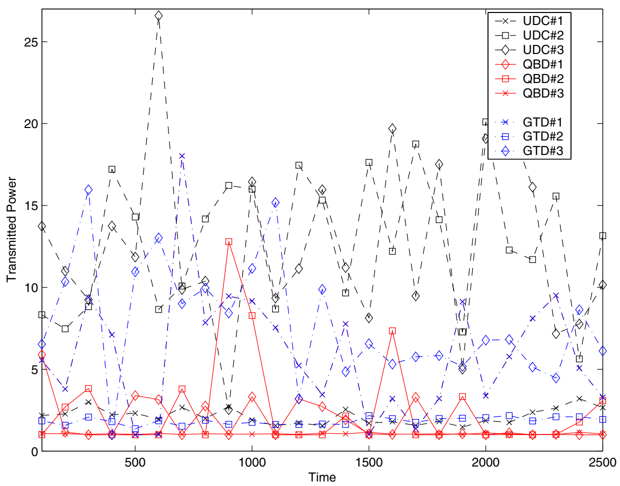

Fig. 5. Instant transmission power per user for the data packets QBDPC, GTDPC and UDCPC.

formulates power control as an optimal control problem. Following this "queue" paradigm, a computationally efficient *queue-based distributed power control (QBDPC)* algorithm has been devised and its theoretical properties have been analyzed. Simulation results demonstrate the effectiveness of QBDPC compared to existing *SINR-based* algorithms. In particular, it has been seen that QBDPC exhibits comparable performance with significant power savings with respect to the up/down centralized algorithm currently used in WCDMA networks as well as with respect to a recently proposed distributed algorithm based on game theory.

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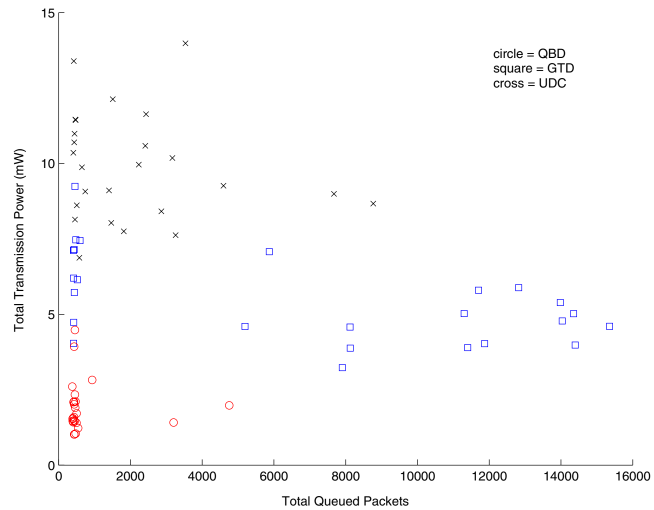

Fig. 6. Average total transmission power versus total queued packets in the system for the QBDPC, GTDPC and UDCPC.

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