A Near-Optimal Multiuser Joint Speech Source-Channel Resource-Allocation Scheme Over Downlink CDMA Networks

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***Abstract*—In downlink of code-division multiple-access (CDMA) networks, the maximal number of real-time calls can be increased by smoothly increasing the end-to-end distortions. In this paper, a cross-layer optimization system is developed to control each user's distortion by adapting source coding rates, channel coding rates, and transmit powers. In addition, the channel-induced distortion is controlled to be only a small proportion of the total end-to-end distortion, such that the subjective quality of the received signal is high. The formulated problem is to reduce the overall end-to-end distortion in downlink single-cell systems, under the constraints of users' maximal acceptable distortions and maximal total transmit power from the base station. To solve this problem, a near-optimal algorithm is constructed to allocate resources. A performance upper bound is developed and compared with the performance of the proposed algorithm. A dynamic system considering speech activities and different offered loads is also analyzed. From the simulation results, the proposed algorithm significantly reduces distortion and the necessary maximal transmit power when the number of users is large, compared with the traditional voice over CDMA schemes.**

***Index Terms*—Channel coding, communication networks, communication protocols, resource management, speech communication.**

I. Introduction

In CODE-DIVISION multiple-access (CDMA) systems, all users transmit simultaneously over the same frequency band using different spread-spectrum codes. Because perfect separation between codes is not achievable for real wireless channels, even for downlink transmission, the capacity and the maximal number of users are limited by interferences among codes. Resource allocation, such as rate adaptation and power control, is an important means to combat interferences, increase the number of users, and maintain the received signals' qualities. For speech data employing joint source and channel coding, rate adaptation by modifying the source and channel coding rates can adjust the source encoders' output qualities and the protections against channel errors. Consequently, the reconstructed signals' qualities can be carefully controlled according to channel conditions. In addition, power control can be used to maintain the received signal-to-interference-plus-noise ratio (SINR). So the problem is how to increase the system performance by effectively allocating the resources among users.

Distortion-based resource allocation is an important research issue for wireless multimedia transmission. In [1]–[3], a source-encoding-assisted multiple-access protocol was developed to selectively drop source packets and increase the system capacity during congestion. In [4], the problems of resource allocation in CDMA were studied for different performance goals. In [5], the overall power was minimized for uplink multicell multimedia systems. In [6] and [7], the system was optimized by defining a utility which was maximized by dynamic pricing and cooperation between mobiles and base stations. In [8], the problem was formulated as a constrained optimization problem using approximations to find a simple solution. In [9], multiple antennas are considered for CDMA multimedia services. There are few existing works for modeling joint source-channel coding and power control in wireless networks to fully use the multiuser diversity. Moreover, most solutions are either based on nonlinear integer optimization or convex optimization methods using convex/linear approximations. These solutions have very high complexity, or the performance highly depends on the accuracy of the approximations. Therefore, it is necessary to develop a simple algorithm with relatively good performance.

From subjective tests using speech sequences, we notice that channel-induced distortions are subjectively more annoying than source coder-induced distortions [10], [11]. In contrast to other joint source and channel coding work, such as [13] and [14] where the overall end-to-end distortion (source-induced distortion plus channel-induced distortion) is minimized, the proposed design goal is to allow the channel-induced distortions to contribute only a small proportion of overall end-to-end distortions, so as to ensure high subjective reconstructed speech quality.

In this paper, we construct a distortion management system for wireless voice communications and develop a near-optimal resource-allocation algorithm in a power-limited downlink single-cell CDMA system. The system is optimized to reduce the overall end-to-end distortion, with the additional constraints of maximal transmit power from the base station, maximal

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distortion that each user can accept, and subjectively better reconstruction quality. Because of the nonlinearity, nonconvexity, and integer properties of the parameters, the formulated problem is NP-hard. Inspired by a daily event, we develop a simple resource-allocation algorithm to manage each user's discrete rates and limited transmit power from the base station. We also develop a tight performance upper bound to evaluate the proposed algorithm. In addition, we explore a dynamic system scenario considering speech activities and different offered loads. From the simulation results, the proposed algorithm significantly reduces the distortions and the necessary maximal transmit power when the number of users is large, compared with the traditional voice over CDMA schemes (with no distortion control). The proposed algorithm has near-optimal performances, compared with a tight upper bound.

The organization of this paper is as follows. In Section II, the system model is given. In Section III, the cross-layer system for voice transmission is described. In Section IV, the problem is formulated and the proposed algorithm is developed. A tight performance upper bound is also developed. In Section V, we evaluate the performance for dynamic systems. In Section VI, simulations studies are presented. And in Section VII, conclusions are drawn.

II. System Model

We consider a system with N users and total bandwidth W for the downlink of a single-cell CDMA system with a fixed transmission rate R. The system is assumed to be synchronous, and each user is assigned a unique pseudorandom code within each cell. Because of the multipath environment, the orthogonality between different codes may not be guaranteed [16], [17]. Each mobile user is subject to intracell interferences from the other users. Over one bit period, the received signal at the ith mobile is given by

$$\tilde{y}_i(t) = \sum_{j=1}^{N} \sqrt{P_j G_i} \sum_{l=1}^{L} \alpha_i^l \left(t - \tau_i^l\right) b_j s_j \left(t - \tau_i^l\right) + n_i(t) \quad (1)$$

where P_j is the transmit power from the base station for the jth mobile, G_i is the path loss to the ith user, α_i^l is the lth multipath fading to the ith user, τ_i^l is the corresponding delay, b_j is the transmit bit, s_j is the signature of the jth user, and n_i is the noise plus intercell interference.

A matched filter is applied with sampling at the chip rate. A Rake receiver is used with finger weights equal to the complex conjugates of each multipath fading. The sum of multipath fading powers is assumed to be unity. The mobiles' thermal noise plus intercell interference are assumed to be white Gaussian with the same variance σ^2 for all users. The SINR of mobile i at the output of Rake receiver is given by

$$\Gamma_i = \frac{W}{R} \frac{P_i G_i}{G_i \sum_{j=1, j\neq i}^{N} \theta_{ji} P_j + \sigma^2} \quad (2)$$

where θ_{ji} is the orthogonality factor which represents the fraction of the received downlink power that is converted by multipath into the intracell interference. The higher the value, the more the orthogonality loss. An accurate instant value for θ_{ji} is impossible to obtain in practice. We assume the fading profiles for all users are the same. In [17], for the independent Rayleigh fading, the average orthogonality factor θ is approximated by

$$\theta = 0.81 - \frac{0.81 \sum_{l=1}^{L} (E(|\alpha^l|^2))^2}{\left(\sum_{l=1}^{L} E(|\alpha^l|^2)\right)^2}. \quad (3)$$

III. System Description

Fig. 1 shows the block diagram of the proposed cross-layer system which is located at the base station. Among users, the system is optimized to fully use the multiuser diversity and to manage interferences by controlling different users' source rates, channel coding rates, and transmit powers. For each user, the system is operated in such a way that the distortion due to channel-induced errors should be a small proportion of the overall distortion, so that the system will behave according to the rate-distortion curve of the speech encoder. In doing so, the system considers the effects on the reconstructed signal qualities, and takes into consideration the subjectively more annoying nature of channel-induced random errors. For example, when the channel is bad, there are more transmitted bits assigned to channel protection and fewer bits for source coding. This reduces the channel errors, but increases source-coding distortions. For the reconstructed received voice, this kind of source-coder-induced distortion is subjectively better compared with channel-induced distortions, behaves according to the rate-distortion curve, and can be predictably controlled by the proposed system. Such a dynamic nature is the main difference of the proposed scheme from the traditional joint source and channel coding that minimizes the end-to-end distortion without considering the subjective quality of reconstructed speech. In the rest of this section, we discuss two main modules of the proposed system in detail.

A. Source-Coder Module

In the proposed system, the real-time source encoder has the key property that the output rate can be externally controlled. This can be implemented by using either variable-rate or embedded encoders. In the first case, the coder generates one bit stream for each of the possible encoding rates. Only one of these will be selected and transmitted based on the rate assignment. Using embedded encoders presents the advantage that only one bit stream is generated, making the rate adaptation simply by dropping as many bits as necessary from the end of the bit stream, where less important data are located. Although the "bit dropping mechanism" is exclusive to the embedded stream, this term is used loosely to represent a reduction in the source rate, regardless of the particular source encoder implementation. The source coder is assumed to have the maximal output rate $\eta_{\max}$ b/s. The source rate controller has the output rate rR b/s ($rR \leq \eta_{\max}$), where r is the variable channel coding rate and R is the fixed CDMA transmit rate. Then the data streams are encoded by the channel-coding module. The processing gain for the CDMA spreader is W/R. Binary phase-shift keying (BPSK) modulation is applied with power control at the amplifier.

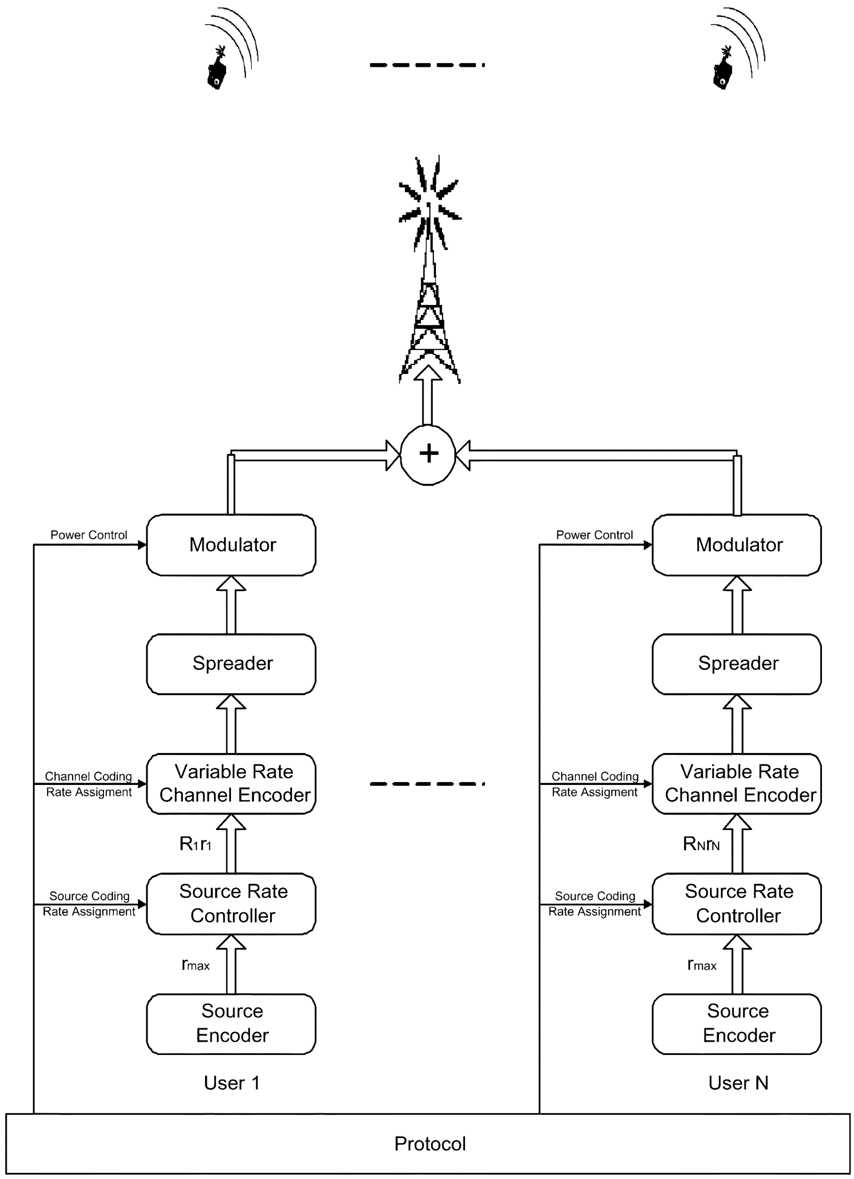

Fig. 1. Block diagram for the proposed system.

Define $D_s(rR)$ as the distortion-rate function of the user's source encoder transmitting at rate rR. In most well-designed encoders, D_s is a convex and decreasing function. The minimum distortion occurs at maximum source rate $\eta_{\max}$. Furthermore, the source codec distortion-rate function [23], [24] is approximated by

$$D_s = \delta 2^{2k(\eta_{\max} - rR)} \tag{4}$$

where δ is the minimal distortion and k is a parameter depending on the encoder. This is a very general form that applies to the case of Gaussian source with mean squared error (MSE) distortion or when the high-rate approximation holds. In the case of realistic encoders, we find that (4) constitutes a good and tight upper bound on the real distortion-rate curve.

B. *Variable-Rate Channel-Coder Module*

We use channel codecs with adjustable rates, in order to jointly adjust rates in both source and channel codecs according to the needs for distortion controls and channel protections. In this paper, a rate-compatible punctured convolutional (RCPC) code [12] is applied for channel coding, because of its wide range of channel-coding rates and simplicity. A family of RCPC codes is described by the mother code of rate $(1/M)$. The output of the coder is punctured periodically, following puncture tables. The puncturing period Q determines the range of channel-coding rates $r = Q/Q + l, l = 1, \ldots, (M-1)Q$ between $(1/M)$ and $Q/Q+1$ with different channel error-protection abilities. Moreover, only one Viterbi receiver is needed for the RCPC codes with different rates, which reduces the system complexity.

For simplicity, all transmitted bits are assumed equally important for error-protection purposes. Unequal error protection can be applied in a similar way. Because channel-induced errors are perceptibly more annoying than source-encoding distortions, the design goal is that channel-induced errors would account for less than a small proportion of the overall end-to-end distortion.

To meet the design goal, the received SINR should be no less than a targeted SINR. At constant transmission rate, a reduction in source-encoding rate allows for a decrease in channel-coding rate, and as a result, increases the channel protection. Thus, the targeted SINR is also a function of the source-encoding rate, or equivalently, a function of the channel-coding rate. In the rest of this subsection, we develop a model for this targeted SINR as a function of rate subject to the design goal.

In order to develop a relation between channel-coding rate and targeted SINR, we analyze a uniform scalar quantizer encoding a uniform source with a random index assignment as an example. In order to keep the analysis mathematically tractable, we only consider two sources of distortions: source encoding (compression) and channel-induced distortions. We will study more complicated and practical encoders through the later simulations. Suppose the input vector $\mathbf{x} \in \Re^K$, where K is the number of samples for each quantization. The output of the source encoder has m bits which determine the source-encoding rate. The source-encoder quantizer distortion can be written as

$$D_s = \sum_{i=1}^{2^m} \int_{S_i} \|\mathbf{x} - \mathbf{y}_i\|^2 P_b(\mathbf{x}) d\mathbf{x} \tag{5}$$

where $\{S_i\}_{i=1}^{2^m}$ is the partition of $\Re^K$ into disjoint regions, $\mathbf{y}_i$ is the quantized vector with index i, and $P_b(\mathbf{x})$ is the probability density function of $\mathbf{x}$. From [23], the source-encoding distortion of such a quantizer is given by $D_s(m) = (2^{-2m}/12)$. Define $q(j|i), i \neq j$ as the probability that the decoded vector index is j, while the transmitted vector index is i. Suppose channel errors happen randomly and independently with respect to the source-encoder index. The probability of decoding error is $P_e = \sum_{j=1}^{2^m} q(j|i)$, which is the same for all i. The overall distortion after the channel decoding at the receiver can be written as

$$D(m, P_e) = \sum_{i=1}^{2^m} \sum_{j=1}^{2^m} q(j|i) \int_{S_i} \|\mathbf{x} - \mathbf{y}_i\|^2 P_b(\mathbf{x}) d\mathbf{x}. \tag{6}$$

From [13] and (6), the expected MSE of the uniform scalar quantizer for a uniform source with a random index assignment is

$$\begin{aligned} D(m, P_e) &= \frac{2^{-2m}}{12} + \frac{P_e}{6}(1 + 2^{-m}) \\ &\approx D_s(m) + \frac{P_e}{6} = D_s(m) + D_c \end{aligned} \tag{7}$$

where the second term is the channel-induced distortion which is defined as D_c.

Define ζ as the proportion of channel-induced distortion over the overall distortion. In order to implement the design goal $(D_c/D) \leq \zeta$, we need to let the system achieve some targeted error probability P_e^t. Obviously, $P_e = P_e^t$ when the system converges. From (7), we can write P_e^t as

$$P_e^t = \frac{6\zeta D_s(m)}{1 - \zeta} = \frac{\zeta 2^{-2m}}{2(1 - \zeta)}. \tag{8}$$

Next, we briefly analyze the actual error probability P_e for RCPC codes. P_e is determined by the channel condition, coding structure, and SINR at the receiver. For the channel model in (1), with BPSK modulation and Hamming distance d, the conditional pairwise error probability conditioned on the fading parameters $\{\alpha_i\}$ in (1) is given by [15]

$$P_e(d|\{\alpha_i\}) = Q(\sqrt{2\Gamma}) \tag{9}$$

where Γ is the SINR. Then the average error probability over fading channel statistics is given by

$$P_e(d) = \left(\frac{1 - \mu}{2}\right)^d \sum_{k=0}^{d-1} \binom{d - 1 + k}{k} \left(\frac{1 + \mu}{2}\right)^k \tag{10}$$

where $\mu = \sqrt{(\Gamma/1 + \Gamma)}$. When $\Gamma \gg 1$, the above equation can be simplified as

$$P_e(d) \approx \left(\frac{1}{4\Gamma}\right)^d \binom{2d - 1}{d}. \tag{11}$$

From [14], a tighter upper bound for any coded frame lengths larger than the constraint length is given by

$$P_e \approx \sum_d ((l_{m'} - 1)a_d + b_d) P_e(d) \tag{12}$$

where m' is the information frame size, $l_{m'}$ is the number of branches of the trellis that are in a frame, and the values of a_d and b_d can be found in [12] and [14].

The system will allocate resources such that the actual bit-error rate (BER) is the same as the targeted BER, i.e., $P_e = P_e^t$. Since P_e is a function of SINR in (2), and P_e^t is a function of r in (8), we can get the relation between the SINR and channel-coding rate. We plot the relation of Γ in decibels versus channel-coding rate in Fig. 2, for an RCPC code with memory 4, puncture period 8, where there are 20 information bits per frame, the transmit rate is 24.4 kb/s, $K = 1, m = 8$, and $\zeta = 0.03$. The curve shows an almost linear relation. This is because (8) is an exponential form of m, and consequently, an exponential form of channel-coding rate r, while (12) is a sum of polynomials in Γ. Furthermore, through simulations using different configurations of RCPC codes and practical source encoders (one of which is shown in Fig. 2),[1] the targeted SINR as a function of channel-coding rate, when the design goal is achieved, can be approximated accurately by

$$\gamma \approx 2^{Ar+B} \tag{13}$$

where γ is the required targeted SINR, and A and B are fixed parameters of the error-control coding and ζ. The received SINR should be no less than this targeted SINR, i.e., $\Gamma \geq \gamma$.

[1]Notice that two sets of curves have similar linearity but different values, because the source coders are different.

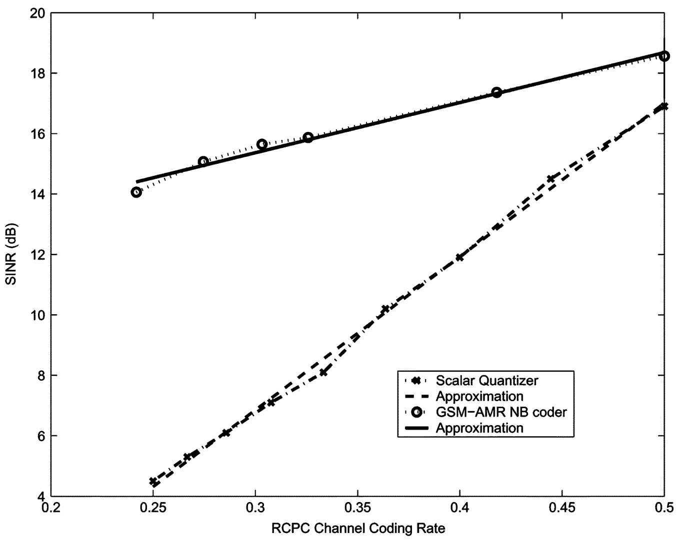

Fig. 2. Required SINR versus RCPC rate with $\zeta = 0.03$.

IV. Real-Time Distortion Management

A. Problem Formulation

In practice, the transmit power from the base station is bounded, because of limitations of the power amplifier and concerns for co-channel interference to other cells. When the system is loaded, even with the maximal transmit power, the system cannot allow every user to operate at their minimal distortions. Under this condition, it is necessary to have a graceful distortion control: the users with relatively low distortions, in bad channel conditions, or generating too much interference to others, need to sacrifice their performances slightly by increasing their distortions in a controlled way. By doing so, the system will use the limited transmit power to reduce the interferences, optimize the overall system performance, and increase the total number of users. The problem is to decide who will be sacrificed and how to minimize the distortions.

In the rest of this paper, we normalize each user's distortion with the minimal distortion without channel-induced errors. The ith user's normalized distortion is denoted as D_i. The goal is to minimize the overall system distortion, under the constraints that each user's distortion is smaller than a maximal acceptable value $D_{\max}$, the overall transmit power $P_{\text{sum}} = \sum_{i=1}^{N} P_i$ from the base station is bounded by the maximal transmit power $P_{\max}$, and channel-induced distortion is less than ζ of total distortion. Define D_i, D_i^s, and D_i^c as the overall end-to-end distortion, source-induced distortion, and channel-induced distortion for user i, respectively. The problem is formulated as

$$\min_{r_i} \sum_{i=1}^{N} D_i \tag{14}$$

$$\text{subject to} \begin{cases} \text{Distortion range} : 1+\zeta \leq D_i \leq D_{\max} \quad \forall i \\ \text{Transmit power} : P_{\text{sum}} \leq P_{\max}, \\ \qquad\qquad D_i^c \leq \zeta D_i = \zeta(D_i^c + D_i^s) \quad \forall i. \end{cases}$$

Without loss of generality, all users are assumed to have the same $D_{\max}$ for simplicity. Here r_i is implicitly constrained by the combination of (4) and the above distortion-range constraint.

The optimization variables r_i's are discrete. The optimization goal and the constraints in (14) are nonlinear and nonconvex. So there might be many local minima, and no Lagrangian-based solution is available in the literature. Moreover, the computation complexity will grow quickly with the number of users, if the solutions are based on nonlinear integer programming. The problem can be reformulated as a *knapsack* problem [31], which is known to be NP-hard. In order to implement an efficient solution with less computational burden in a real-time CDMA system with a large number of users, it is necessary to develop a fast algorithm with a relatively good performance.

B. Pizza Party Algorithm

The intuitive idea to develop a fast algorithm comes from a daily event. For example, in a pizza party with limited available pizzas, if the number of people is small, everybody should have enough pieces and there might be some pizzas left. However, if the number of people is large and there is no way that everybody will be well satisfied, it is necessary to decide how to allocate the pizzas such that overall, people's satisfactions are high. The problem is similar to (14) in that D_i represents a user's dissatisfaction level and P_{sum} is similar to the overall amount of pizzas. A person will increase his/her satisfaction by getting more pizzas, like a user will decrease its distortion by consuming more power. A possible solution for pizza allocation is to first let everybody eat the minimal piece. (We assume there are enough pizzas for this requirement.) Then, for example, we will let kids eat one more slice of pizza, because they can eat less pizza and get satisfied more easily. If there are any pizzas left, we will give one slice per time to the people who can be satisfied most easily then. (Probably elder people will get pizzas next, then ladies, and finally young gentlemen.) By allocating pizzas in such a way, we can use the limited pizzas to let the overall satisfaction be high. We believe this approach can also be applied to solve the proposed problem in (14) with high efficiency and optimality. In the rest of this section, we will quantify the pizza party allocation idea using mathematical representations.

The criterion for pizza party allocation is to find the person who can eat less while becoming satisfied easily. Similarly, we need to find the user who can demand less power while reducing its distortion most. To quantify this, we need to find the differential of the overall transmit power P_{sum} with respect to each user's distortion. Since the constraint $D_i^c \leq \zeta D_i \ \forall i$ is satisfied by the approximation in (13), the optimization goal in (14) is equal to minimize $\sum_{i=1}^{N} D_i^s$. From (2), the overall power that satisfies $\Gamma_i \geq \gamma_i \ \forall i$ can be written in a matrix form [5]

$$P_{\text{sum}} = \mathbf{1}^T[\mathbf{I} - \mathbf{F}]^{-1}\mathbf{u} \tag{15}$$

where $\mathbf{1} = [1 \cdots 1]^T, \mathbf{I}$ is an $N \times N$ identity matrix, $\mathbf{u} = [u_1, \ldots, u_N]^T$ with $u_i = \sigma^2 T_i / G_i$, and

$$[\mathbf{F}]_{ij} = \begin{cases} 0, & \text{if } j = i \\ \theta_{ji} T_i, & \text{if } j \neq i \end{cases}$$

where

$$T_i = \frac{2^{Ar_i+B}R}{W} = \frac{P_i G_i}{G_i \sum_{j\neq i} \theta_{ji} P_j + \sigma^2}. \tag{16}$$

If the processing gain is large, i.e., W/R is large, T_i is a small number. Since $0 < \theta_{ji} < 1, \theta_{ji} T_i$ is also a small number. A simple approximation for P_{sum} is thus given by

$$P_{\text{sum}} \approx \mathbf{1}^T[\mathbf{I}+\mathbf{F}]\mathbf{u} = \sum_{i=1}^{N} \frac{\sigma^2 T_i}{G_i} + \sum_{i=1}^{N}\sum_{j\neq i}^{N} \frac{\sigma^2 \theta_{ji} T_i T_j}{G_j}. \tag{17}$$

The gradient of the overall transmit power with respect to each user's source-encoding distortion can be written as a function of the following three differentials:

$$g_i = \frac{\partial P_{\text{sum}}}{\partial D_i^s} = \frac{\frac{\partial P_{\text{sum}}}{\partial T_i}\frac{\partial T_i}{\partial r_i}}{\frac{\partial D_i^s}{\partial r_i}} \tag{18}$$

where

$$\frac{\partial P_{\text{sum}}}{\partial T_i} = \frac{\sigma^2}{G_i} + \sum_{j\neq i}^{N} \frac{\sigma^2 \theta_{ji} T_j}{G_j} \tag{19}$$

$$\frac{\partial T_i}{\partial r_i} = \frac{AR2^{Ar_i+B}\ln 2}{W} \tag{20}$$

$$\frac{\partial D_i^s}{\partial r_i} = -2kR2^{2k\eta_{\max}}2^{-2kr_iR}\ln 2. \tag{21}$$

So the final gradient can be written as

$$g_i = C2^{(A+2kR)r_i}\left(\frac{1}{G_i} + \sum_{j\neq i}^{N} \frac{\theta_{ji} T_j}{G_j}\right) \tag{22}$$

where C is a negative constant. The absolute value of g_i is determined by three factors: the current rates (the factor before the parentheses); the channel gain (the first term inside the parentheses); and the interferences to others (the second term inside the parentheses).

Similar to the pizza allocation method we mentioned above, we allocate the rates and powers in the following way. If $P_{\max}$ is large enough for every user in the cell to have the minimal distortion, $D_i^s = 1$ is assigned to everybody and there might be some overall transmit power left.

If $P_{\max}$ is not large enough for everybody to have the minimal distortion, $D_i = D_{\max}\ \forall i$ will be initially assigned. If the power is still not enough, it means that there is not enough power to satisfy the group's minimal needs and an outage is reported. If there is some power left, we will see who can reduce its distortion more and consume less transmit power by determining the absolute value of the gradient g_i. For such a selected user, from (22), its current rate is low (i.e., the distortion is high), its channel gain is good, or its interferences to others are small. Consequently, this user deserves a smaller distortion. In other words, this user can reduce its end-to-end distortion while creating the smallest strain on the available resources. So a higher source rate (higher r_i) is assigned to this user to let the distortion become small. Then the gradient is estimated and the rate is assigned again. This process is continued until the power is used up; i.e., no user can increase its rate without making the overall power in the base station greater than $P_{\max}$. By doing this, the distortions are reduced by consuming the minimal resources step by step.

TABLE I
PIZZA PARTY ALGORITHM

1. Initialization: If everybody can get $D_i^s = 1$, then allocate the powers and stop; else allocate D_{max} to everybody. If $P_{sum} > P_{max}$, report an outage.
2. Repeat: • Calculate $\|g_i\|$. • Increase the rate of the user with smallest $\|g_i\|$ to the next available discrete rate, unless the rate is the maximal rate already. • If $P_{sum} > P_{max}$, return the previous rate allocation and break.
3. Rate and Power Assignment.

On the whole, the proposed algorithm is given in Table I. As mentioned before, to solve the NP-hard problem in (14) by means of traditional methods, such as the branch-and-bound algorithm [31], the complexity grows fast with the number of users N increasing. In the proposed algorithm, the complexity lies in calculating the overall transmit power in (17) and computing the gradients in (22). The complexity is $O(N^2)$, and so the proposed algorithm can be easily implemented in practice. In addition, we can apply the average orthogonality factor θ in (3) to all θ_{ji} in the pizza party algorithm, so that there is no need to estimate the real-time orthogonality factor, which is a complex task.

C. Performance Upper Bound

In order to evaluate the optimality of the proposed algorithm, we provide a performance upper bound. This bound has a better result than the optimal solution of (23) and is computable. However, it cannot be implemented in practice, and can only serve to compare with the proposed scheme. If the proposed algorithm has a similar performance to that of the bound, we can conclude that the proposed algorithm is at least near-optimal and the performance upper bound is also tight. To obtain the upper bound, the channel-coding rate is relieved to be a continuous variable, so that the problem in (14) becomes a nonlinear constrained problem and has a better performance than the optimal solution of (23). Then some nonlinear optimization methods can be used to solve it. The modified problem definition with the continuous relaxation of (14) can be expressed as

$$\min_{r_i} \sum_{i=1}^{N} 2^{-2kRr_i} \quad \text{subject to} \begin{cases} r^{\min} \leq r_i \leq r^{\max} & \forall i \\ P_{\text{sum}} \leq P_{\max} \end{cases} \tag{23}$$

where $r^{\min}$ and $r^{\max}$ are the minimal/maximal channel-coding rate that generates the maximal/minimal distortion, respectively. From (16) and (17), the power constraint is a nonlinear function of r_i. $r^{\max}$ is equal to the maximal RCPC coding rate which generates the minimal distortion, and

$$r^{\min} = \frac{\eta_{\max}}{R} - \frac{1}{2kR}\log_2{(1-\zeta)D_{\max}} \tag{24}$$

which generates the maximal distortion $D_{\max}$.

In order to solve (23), a barrier method combined with the Newton method [18] is applied. The approach for the barrier method is to add barrier functions to the optimization goal such that the constrained optimization problem becomes the unconstrained optimization problem. The sum of optimization goal and barrier function approaches infinity if the constraints are not satisfied. On the other hand, if the constraint is satisfied, the barrier function does not affect the optimization goal. The barrier function is commonly approximated by logarithmic barrier functions [18]. In the proposed problem, the barrier function is composed of three elements, and is given by

$$I_{\text{constaint}} \approx \Phi_1 + \Phi_2 + \Phi_3 \tag{25}$$

where Φ_1 is for minimal channel-coding rate, Φ_2 is for maximal channel-coding rate, and Φ_3 is for maximal overall power. They have the forms of

$$\Phi_1 = \begin{cases} -\sum_{i=1}^{N}\ln(r_i - r^{\min}), & r_i > r^{\min} \\ \infty, & \text{otherwise} \end{cases} \tag{26}$$

$$\Phi_2 = \begin{cases} -\sum_{i=1}^{N}\ln(r^{\max} - r_i), & r^{\max} > r_i \\ \infty, & \text{otherwise} \end{cases} \tag{27}$$

$$\Phi_3 = \begin{cases} -\ln(P_{\max} - P_{\text{sum}}), & P_{\max} > P_{\text{sum}} \\ \infty, & \text{otherwise.} \end{cases} \tag{28}$$

The basic idea of the barrier-method approach is to solve the constrained optimization problem by a sequence of unconstrained problems. First, an unconstrained optimization problem is formulated as the optimization goal plus the barrier function. The solution can be found by a standard solution, such as the Newton method [18]. Then, in the next iteration, the barrier function is modified such that it is closer to the real constraints. The new unconstrained optimization problem is formed using this modified barrier function. The unconstrained optimization is initialized by the results in the previous iteration. This sequence of optimizations is continued until convergence. In each iteration, rewrite (23) as the unconstrained optimization problem as

$$\min_{r_i} f = \tilde{t}\sum_{i=1}^{N} 2^{-2kRr_i} + I_{\text{constraint}} \tag{29}$$

where $\tilde{t}$ is a value that increases from iteration to iteration. The barrier functions become more and more like the ideal barrier function as $\tilde{t}$ increases. So the solution is more and more optimal. Define $\mathbf{r} = [r_1 \cdots r_N]^T$; the algorithm is given in Table II, where $\tilde{m}$ is the iteration number for the barrier method, ϵ determines the accuracy of the proposed algorithm, t' is the optimal step for the Newton method, t_0 is the initial value for the barrier function whose value determines the convergence rate of the first iteration, and $\beta > 1$ is the constant that multiplies $\tilde{t}$ in each iteration.

TABLE II
BARRIER METHOD FOR PERFORMANCE BOUND

1. Initial:
$\mathbf{r}$ = any feasible value, $\tilde{t} = t_0 > 0$, $\beta > 1$, $\epsilon > 0$.
2. Repeat:
• Start at $\mathbf{r}$, compute new $\mathbf{r}$ by minimizing f, using **Newton Method**:
1. Compute Newton step $\mathbf{v}_{nt}$ and decrement λ^2.
$\mathbf{v}_{nt} = -\bigtriangledown^2 f^{-1} \bigtriangledown f$
$\lambda^2 = \bigtriangledown f^T \bigtriangledown^2 f^{-1} \bigtriangledown f$
2. quit if λ^2 is stable.
3. Line search: compute step size t' by backtracking line search.
4. Update: $\mathbf{r}$=$\mathbf{r}$+t'*$\mathbf{v}_{nt}$.
• if $\tilde{m}/\tilde{t} < \epsilon$, return $\mathbf{r}$.
• $\tilde{t} = \beta\tilde{t}$.

The performance bound algorithm in Table II cannot be implemented in practice. This is because the rate is assumed to be continuous, which is not true in a real channel codec. In addition, the complexity of this algorithm is much higher than the proposed algorithm in Table I. The complexity lies in that in order to find the solution, one iteration is needed for the Newton method and another iteration is needed for the barrier method. Moreover, because the problem in (23) is nonlinear and nonconvex, there might be many local optima. Multiple initializations or even annealing are necessary to find the global optimum. Nevertheless, the algorithm in Table II can be used to compare the performance of the proposed fast algorithm in Table I. Because of the continuous channel-rate assumption, the performance bound has a better performance than the real optimal solution in (14), while the real optimal solution has a better performance than the proposed algorithm. In the simulations in Section VI, we will show that the proposed algorithm has similar performances to the performance bound. So not only is the proposed greedy algorithm near-optimal, but also, the performance upper bound is tight.

V. Dynamic System

In the previous sections, the resource-allocation algorithm is developed to reduce the overall distortions with a fixed number of users in the system. In this section, the dynamic traffic case is considered, where the number of admitted calls changes and the different speech activities are considered. Finally, a Monte Carlo method is constructed to analyze the system performance.

We assume that users arrive at random following a Poisson distribution, with average arrival rate λ. The holding time for each call is modeled as an exponential random variable with parameter μ. The number of admissible users is bounded by

TABLE III
MONTE CARLO METHOD FOR DYNAMIC SYSTEM

1. Random Generation: Generate the calls and channel conditions.
2. Admission Control: Given λ and μ, calculate N_{max} and blocking probability P_b by threshold d.
3. Speech Activity: Determine the state of speech and assign different normalized distortion.
4. Pizza Party Algorithm: Find the rate and power allocation by the proposed algorithm.
5. Accumulate Results: Accumulate results and repeat from step 1, until sufficiently accurate.

the processing gain. In order to determine the maximal number of admitted users $N_{\max}$, we use the average distortion per call $E(D)$. Specifically, the call admission policy is that $N_{\max}$ is selected such that $E(D) \leq d$, where d is a given threshold. Moreover, $N_{\max}$ is less than or equal to the processing gain, which is the maximal number of available spreading codes.

Suppose N is the number of users in the system. From [19], N is a truncated Poisson $(\rho, N_{\max})$ random variable, where $\rho = \lambda/\mu$. For $n = 0, 1, \ldots, N_{\max}$, the stationary probability that the system has n ongoing users is given by

$$P[N = n] = \frac{\frac{\rho^n}{n!}}{\sum_{i=0}^{N_{\max}} \frac{\rho^i}{i!}}. \tag{30}$$

By the Poisson arrivals see time averages (PASTA) property [19], the blocking probability is given by $P_b = P[N = N_{\max}]$.

From the previous section, the overall distortion with a fixed number of users is known, i.e., $E(D|N = n)$. By using the distribution in (30), the average distortion per call is expressed as

$$\begin{aligned} E[D] &= E[E(D|N = n)] \\ &= \sum_{n=0}^{N_{\max}} E(D|N = n)P[N = n]. \end{aligned} \tag{31}$$

In addition to considering that the number of users changes over time, we also take into account that the level of speech activity changes during a conversation. For example, it has been observed that silence periods account for approximately 65% of all time of a two-way communication [21]. Based, on this observation, in this paper, we will model speech as a two-state Markov chain [22]. In this model, one state will represent the silence status, and the other, a talk spurt. The transition probability from talk state to silence state is ε, and the transition probability from silence state to talk state is κ. The transition probability $\varepsilon = 1 - e^{-\Delta/t_1}$ and $\kappa = 1 - e^{-\Delta/t_2}$, where Δ is the frame duration, t_1 is the average talk spurt duration, and t_2 is the average silence duration.

Because each state represents different levels of speech activity (or energy), the bit rate necessary during encoding to achieve some level of distortion also differs. During a silence period, it is not efficient to encode speech at high bit rates. Moreover, those users in a period of silence could be assigned the lowest possible amount of resources without affecting the perceptual quality. At the same time, this assignment would reduce the overall load on the network. Therefore, we adapted the algorithm described in the previous sections to use these observations to increase efficiency. In the improved algorithm, we only adapt those users in a talk spurt, while those in a silence period are always assigned with the minimum source-encoding rate.

As mentioned in the previous subsection, it is impossible to find an analytical expression for $E(D|N = n)$. In order to evaluate the system performance, a Monte Carlo method is shown in Table III. The simulation is run for a sufficiently large number of runs so that stable performance results are obtained with sufficient accuracy.

VI. SIMULATION RESULTS

To simulate the real-time wireless voice communications, we use 18 sequences, both male and female speakers, from the National Institute of Standards and Technology (NIST) speech corpus [25]. These sequences are encoded using the GSM adaptive multirate (AMR) narrowband (NB) speech encoder [26]. This encoder operates with 20 ms frames, 5 ms lookahead, and includes an error-concealment mode. Of the eight possible encoding rates, 12.2, 10.2, 7.95, 7.4, 6.7, 5.9, 5.15 and 4.75 kb/s, the six highest ones are used.

To determine the end-to-end distortion, we choose a perceptually weighted log-spectral distortion measure [28] calculated by numerical approximation of the function

$$SD(\hat{A}(f), A(f)) = \sqrt{\int |W_B(f)|^2 \left| 10 \log \frac{|\hat{A}(f)|^2}{|A(f)|^2} \right|^2 df} \tag{32}$$

where $A(f)$ and $\hat{A}(f)$ are the fast Fourier transform (FFT)-approximated spectra of the original and the reconstructed speech

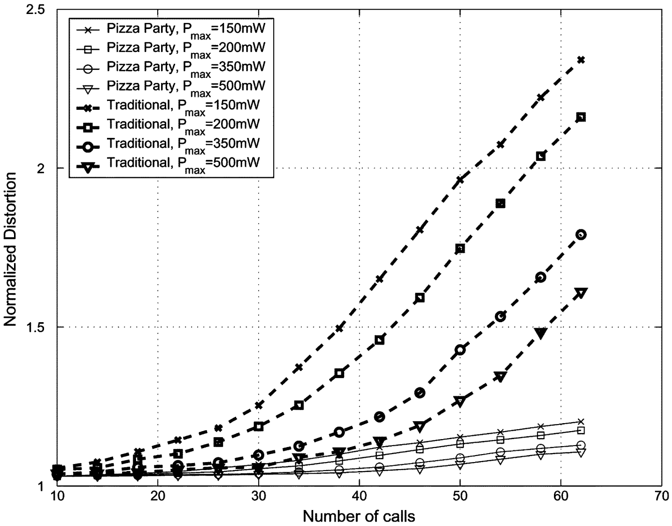

Fig. 3. Normalized distortion versus number of users.

frames, and $W_B(f)$ is the subjective sensitivity weighting function [27]

$$W_B(f) = \frac{1}{25 + 75(1 + 1.4(f/1000)^2)^{0.69}}. \tag{33}$$

This distortion is measured on a frame-by-frame basis and then averaged over all frames, including outliers to further capture the effects of channel errors. This measurement is chosen not only because of its good mathematical properties, but also because of its good correspondence to subjective measures.[2] To report results, we use a normalized distortion measure, which is computed as the ratio of the spectral distortions to that of the speech sequence encoded at the highest rate ($\eta_{\max} = 12.2$ kb/s) without channel noise.

Also, for the proposed system, BPSK modulation is assumed. For the RCPC channel codec, a memory 4, puncturing period 8, mother code rate-1/4 RCPC code in [12] is decoded with a soft Viterbi decoder. The total bandwidth W is 1.5616 MHz. The channel is assumed to be affected by normalized Rayleigh fading (average power loss equal to 1), and normalized path loss (with propagation constants assumed equal to 1) with a path-loss exponent of 3. The cell radius is 500 m. Background noise level was assumed equal to 10^{-6} mW. $k = 3.3 \cdot 10^{-5}$. Processing gain is 64. The transmit rate is 24.4 kb/s. We apply an average orthogonal factor equal to 0.9, as shown in [32].

Fig. 2 shows the targeted SINR, in $\log_2$ scale, as a function of the RCPC channel-encoding rate, where the channel-induced distortion is less than 3% of that of the end-to-end distortion, i.e., $\zeta = 0.03$. The figure shows the different operation modes for the GSM-AMR NB coder in the proposed system. In order to achieve the design goal, the required SINR is a function of the RCPC channel-coding rate. As we can see from the figure, the approximation in (13) is a good approximation for the qualitative behavior of the practical voice encoder, as well. Notice that the curve of the GSM-AMR NB coder simulations differs from that of the analysis results in Section II. This quantitative difference is due to, in part, not including modeling and error-concealment distortion in the analysis results. Nevertheless, both results suggest that the linear approximation in log scale is a good choice for the relation in (13).

For comparison, we set up a traditional CDMA system [29] which shares the same configurations as the proposed scheme, but operates without changing mode, i.e., all users operate in the mode with 12.2 kb/s source-coding rate and channel-coding rate 1/2. From the samples obtained by the simulations available from [30], we observe that the proposed system presents a better performance, in terms of perceived voice quality, than the traditional system with no adaptation. This is because the channel-induced distortion in the proposed system is limited by design to a small proportion of the end-to-end distortion, making the reduction in the source-encoding rate the dominant phenomena in increasing distortion. Therefore, in the proposed system, the increase in distortion subjectively manifests as a smooth degradation of voice quality that hardly affects intelligibility. In contrast, the traditional system with no adaptation is unable to maintain channel-induced distortion at small values. As the system becomes highly loaded, the channel-induced distortion becomes the dominant phenomena in increasing distortion. Subjectively, this is perceived as speech deformation, artifacts, and phantom tones that tend to be annoying and affect intelligibility.[3] We select $\zeta = 0.03$ in the simulations, because channel-induced distortions are limited to a subjectively acceptable range.

Fig. 3 shows the normalized distortion versus the number of users with different transmit powers for the proposed and traditional schemes. When the number of users is small, all schemes with different power have similar normalized distortions. This is because there is enough power for everybody to operate at the minimal distortion. When the number of users is increased, the proposed scheme can reduce the normalized distortion significantly, when compared with the traditional system. This is because the proposed scheme controls the distortion smoothly by adapting the source and channel coding rates. In particular, if, for example $P_{\max} = 350$ mW, the proposed system can support 30 users with 6% less distortion, 40 with 12%, and 50 users with 37% less distortion. When the transmit power is increased, the distortion will be reduced. In Fig. 4, we compare the normalized distortion as a function of the maximal available power for a fixed number of users in the system ($N = 30, 40, 50$, respectively) that represents different network loading conditions. It shows the proposed system can deliver the same level of average end-to-end distortion at a much lower maximum transmit power, especially when the number of users is large.

In order to evaluate the performance of the proposed fast algorithm, we compare the results with the performance of the upper bound in Table II. We define the relative difference as the absolute value of the difference between the average distortion of the proposed algorithm and the upper bound divided by the average distortion of the upper bound. In Fig. 5, we show the relative difference versus the number of users. We apply multiple initializations to get the global optimization by the upper

[2]It is worthy of mention that the encoders in transmitters still encode according to the distortion defined in (5).

[3]For traditional joint source-channel coding, this problem may also exist, since there is no design constraint for channel-induced errors.

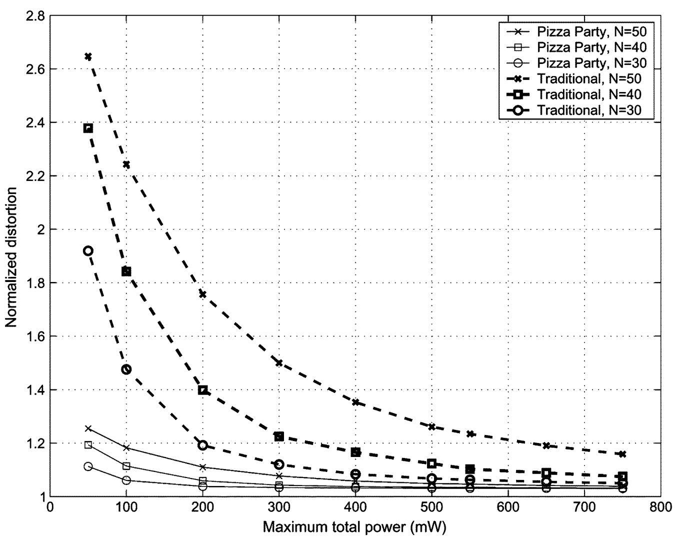

Fig. 4. Normalized distortion versus $P_{\max}$.

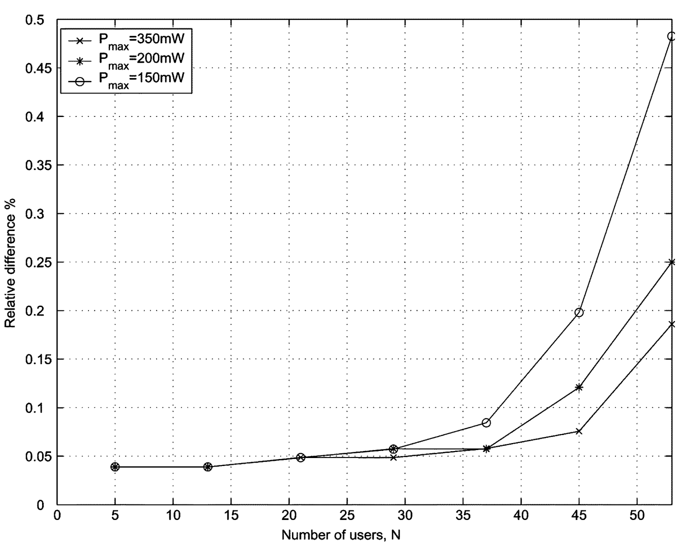

Fig. 5. Relative difference versus number of users.

bound algorithm in Table II. Since the channel rate is assumed continuous for the algorithm in Table III, the global optimum is always better than the global optimum defined in (14). Our proposed algorithm is suboptimal. But when we compare the performance of the proposed algorithm and the upper bound, the difference is less than 0.5%. This proves that the proposed algorithm is at least near-optimal, and the performance upper bound is tight. The performance gets worse when the number of users increases, because of two reasons. First, with an increasing number of users, there exist more and more local optima and the proposed algorithm may fall into some local optimum. Second, in practice, the adaptation changes in the proposed algorithm is limited to a discrete number of possibilities; as the system becomes increasingly loaded, it becomes harder to find adaptations that would reduce distortion while not exceeding the constraints. This is not the case for the upper bound, since the coding rates are assumed continuous.

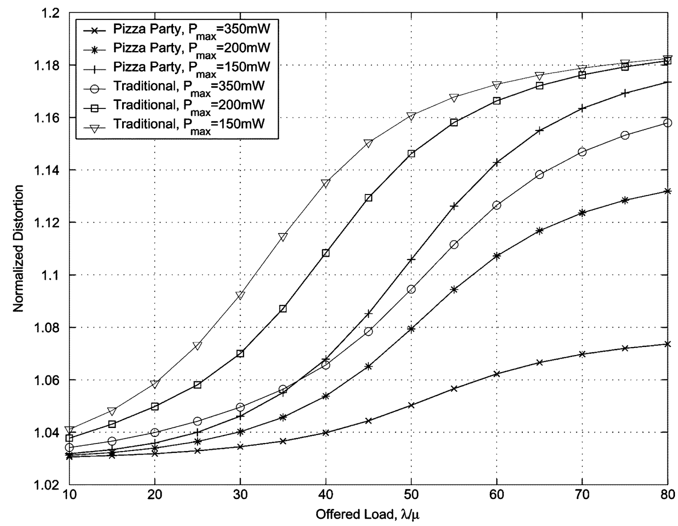

Fig. 6. Dynamic system: Normalized distortions with $d = 1.2$.

For the dynamic system, the offered load is defined as $\rho = \lambda/\mu$, where $\mu = 180$ s. The average talkspurt duration is 1 s, and the average silence duration is 1.35 s. Frame duration Δ is 20 m. $\eta^s_{\max} = 4.75$ kb/s. The admission policy is $d = 1.2$. This distortion value was chosen after simulations so as to ensure that speech subjective quality remained acceptable. In Fig. 6, we show the normalized distortion versus the offered load. We compare the proposed algorithm versus the fixed algorithm for $P_{\max} = 150, 200,$ and 350 mW, respectively. We can see that the normalized distortions increase with the offered load growing, while the proposed algorithm provides much lower distortions. Compared with the static results in Fig. 3, the distortions are greatly reduced by exploiting system dynamics and speech dynamics.

VII. Conclusions

In this paper, we develop a system to smoothly control each user's distortion by varying the source-coding rate, channel-coding rate, and transmit power in a downlink single-cell CDMA system. We propose a design goal that ensures a better subjective reconstruction quality. Then we develop a fast algorithm to reduce the system overall distortion under the maximal transmit power, maximal user's distortion, and subjective quality constraints, according to different users' current rates, channel conditions, and interference to others. The proposed algorithm is near-optimal, compared with a tight performance upper bound. We also explore the dynamics of system and speech activity. Compared with the traditional voice over CDMA scheme without distortion control, the proposed scheme can greatly reduce the distortion and the required power, which, in turn, will increase the maximal number of admissible users.

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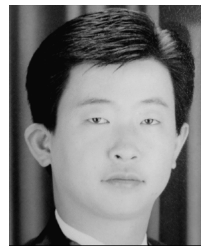

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