A Distributed Power Control Algorithm for Time Varying Wireless Networks with Partially Observable Feedback

Siamak Sorooshayari
Lucent Technologies - Bell Laboratories
67 Whippany Road, Whippany, NJ 07981

Abstract—Adaptive allocation of transmit power has been shown to be an effective means of providing service to competing users with heterogeneous requirements in a wireless network. In this paper distributed stochastic power control is presented for time varying wireless networks with partially observable feedback. With the presented algorithm, a user shall perform interference estimation prior to adapting transmit power so as to address user-centric and network-centric objectives. Aside from the random link gains, detrimental such as noisy feedback and the loss of feedback from the receivers to the transmitting users are considered in the derivation. The closed-loop algorithm is of reasonable complexity thus allowing for distributed online implementation.

I. INTRODUCTION

Dynamic adaptation of transmission power has been researched as a technique for improving the performance and capacity of wireless networks. The importance of distributed methods for power control has traditionally been fueled by the application to the uplink power control problem in cellular systems. More recently, attention has been focused on the application of power control to ad hoc wireless networks which lack infrastructure. A critical issue which has received limited attention pertains to whether the considered power control techniques will be robust to the stochastic impairments of the wireless channel. In fact, a common theme in works on power control for multiple access systems has been the assumption of deterministic channel gains between transmitters and receivers [1], [2]. Such an assumption has been incorporated most so for simplicity rather than the channels actually being static during the convergence of the algorithms.

In this paper, the time varying nature of the channels between the transmitters and receivers are accounted for in the presentation of a distributed stochastic power control algorithm. Imperfections in the feedback channel separating a user and its intended receiver are dynamically modeled, and considered in the design of the algorithm. The estimator-based power control technique presented in this paper is optimal with respect to a user adapting power so as to minimize an objective function consisting of the user’s quality of service (QoS) degradation and the network interference. Furthermore, the presented algorithm is of reasonable complexity since a user will require information pertaining to its interference rather than its stochastic link gains. The remainder of this paper is organized as follows. Section II derives a state-space model of a dynamic system representing stochastic power control in a time varying wireless network with partially observable feedback. The distributed power allocation policy and the corresponding closed-loop power control algorithm are presented in Section III. In Section IV simulation results are provided which illustrate the robustness and utility of the algorithm.

II. DYNAMIC SYSTEM MODEL

A multiple access wireless network is frequently modeled as a collection of radio links separating transmitters and receivers. Each user is characterized as having an intended receiver, with its transmission causing interference to the signals of the other transmitting users. Within a wireless network, the signal-to-interference ratio (SIR) determines a user’s QoS for a given transmission rate and bandwidth allocation. Considering a power control policy with N users of power levels \{P_i(k)\}, at time k, the SIR of the \(i\)th user will be defined as

\[
\gamma_i(k) = \frac{P_i(k)G_{ii}(k)}{\sum_{j \neq i} P_j(k)G_{ij}(k) + \eta_i} = \frac{P_i(k)G_{ii}(k)}{I_{-i}(k)}
\]

with the constant \(\eta_i\) denoting the thermal noise power at the \(i\)th user’s intended receiver. The stochastic nature of the wireless channel is modeled by the multiplicative link gains \(\{G_{ij}(k)\}\), with \(G_{ij}(k)\) denoting the attenuation from the \(j\)th user’s transmitted signal to the \(i\)th user’s intended receiver. With the capacity of current and future wireless networks being interference-limited, the consideration of a user’s interference becomes paramount in protocol design. The \(i\)th user’s perceived interference and aggregate interference will be defined as

\[
I_{-i}(k) = \sum_{j \neq i} P_j(k)G_{ij}(k) + \eta_i
\]

and

\[
I_i(k) = \sum_j P_j(k)G_{ij}(k) + \eta_i = I_{-i}(k) + P_i(k)G_{ii}(k)
\]

respectively. The subscript “−\(i\)” denotes the exclusion of the \(i\)th user’s signal. A common assumption in the formulation of
power control policies is to treat the channel gains as deterministic constants during the convergence of the algorithm. Such a claim is predominantly viewed as being driven by a need for analytical simplification rather than realistic feasibility [3], [4], [5]. In a wireless channel, the fading process and the mobility of the users render the channel response as a stochastic process. Thus, the simplifying assumption of static link gains will be relaxed in this presentation. The time varying nature of the channel shall be depicted by representing each link gain as a stochastic constant during the convergence of the algorithm. Such an assertion is predominantly viewed as being driven by a need for analytical simplification rather than realistic feasibility.

For analytical simplification rather than realistic feasibility, the mobility of the users render the channel response as a stochastic process. Thus, the simplifying assumption of static link gains will be relaxed in this presentation. The time varying nature of the channel shall be depicted by representing each link gain by the first-order Gauss-Markov model

$$G_{ij}(k+1) = G_{ij}(k) + g_{ij}$$

with $g_{ij} \sim N(0, \text{Var}[g_{ij}])$. The stochastic link gains shall be defined as

$$G_{ij}(k) = G_{ij} + \tilde{G}_{ij}(k)$$

with $G_{ij} \triangleq E[G_{ij}(k)]$ representing the path loss, and $\tilde{G}_{ij}(k) \sim N(0, \text{Var}[\tilde{G}_{ij}(k)])$ denoting fluctuations brought on by small-scale effects such as user mobility and multipath fading. Since $0 < G_{ij}(k) \leq 1.0$, the stochastic perturbations shall be limited to the interval $\tilde{G}_{ij}(k) \in (-G_{ij}, 1 - G_{ij})$.

In correspondence with a general interference-based power control ideology, we propose that the $i$th user autonomously adapt power in proportion to its perceived interference via an update of the form $P_i(k+1) = P_i(k) + f\{I_{i,j}(k)\}$. The power update

$$P_i(k+1) = P_i(k) + \alpha_i(k)I_{i,j}(k)$$

supports such a notion, with the gain $\alpha_i(k)$ parameterizing the increase/decrease in transmit power at each time instant. The derivation of the optimal gain $\alpha^*_i(k)$ so as to obtain a desired tradeoff between user-centric and network-centric objectives will be addressed in the following section. After performing an optimal power update of $P_i(k+1) = P_i(k) + \alpha^*_i(k)I_{i,j}(k)$, the $i$th user’s next-step perceived interference can be expressed as

$$I_{i,j}(k+1) = \sum_{j \neq i} P_j(k+1)G_{ij}(k+1) + \eta_i$$

$$= \sum_{j \neq i} (P_j(k) + \alpha^*_j(k)I_{j,k}(k))(G_{ij}(k) + g_{ij}) + \eta_i$$

$$= I_{i,j}(k) + w_i(k)$$

with the stochastic process

$$w_i(k) = \sum_{j \neq i} \alpha^*_j(k)I_{j,k}(k)G_{ij}(k) + P_j(k)g_{ij} + \alpha^*_j(k)I_{j,k}(k)g_{ij}$$

denoting the driving disturbance impinging upon the perceived interference of the $i$th user. Within the network, each transmitting user will receive feedback from it’s intended receiver (i.e. base station) over a dedicated channel which may corrupt and lose the feedback. The feedback will consist of the user’s perceived interference $I_{i,j}(k)$, and shall be provided to the user during each power update. Upon reception of the feedback, the dynamics of the measured interference at the $i$th user is modeled as

$$y_i(k) = [1 + \check{c}_i(k)]I_{i,j}(k) + v_i(k)$$

with $v_i(k)$ denoting the measurement noise incurred during reception, and $\check{c}_i(k)$ a stochastic perturbation representing a loss of feedback at time $k$. Within such framework we have

$$\check{c}_i(k) = \begin{cases} -1 & \text{feedback to user } i \text{ lost} \\ 0 & \text{feedback to user } i \text{ received} \end{cases}$$

with $\check{c}_i(k)$ parameterized by a feedback loss probability $P_{\text{loss}}^i \triangleq P_i[\check{c}_i(k) = -1]$. Realistically, the loss of feedback is inevitable due to the uncertain nature of a wireless link. For instance, transmission errors may render feedback unreliable subsequent to error detection. Furthermore, for delay-sensitive applications, the feedback may be declared lost if its arrival is excessively delayed.

From the above discussion, the stochastic evolution of the $i$th user’s perceived interference can be represented in state-space form as

$$I_{i,j}(k+1) = I_{i,j}(k) + w_i(k)$$

$$y_i(k) = [1 + \check{c}_i(k)]I_{i,j}(k) + v_i(k)$$

with $I_{i,j}(k)$ depicting the state variable, $y_i(k)$ denoting the state measurement, $v_i(k)$ as the measurement disturbance, $w_i(k)$ as the driving disturbance, and $\check{c}_i(k)$ representing a stochastic perturbation to the measurement. Distributed resource allocation typically requires a user to make decisions based on local information which, in this case, is partially observable over an unreliable feedback channel. The remainder of the paper will
be dedicated to the formulation and evaluation of a distributed power control policy for the dynamic system described above and illustrated in Fig. 1.

III. DISTRIBUTED POWER CONTROL ALGORITHM

Within the context of distributed power control we deem a user’s user-centric objectives as benefits that a user may seek with disregard to other network users. Conversely, a user’s network-centric objectives will be characterized as benefits seen by other network users, or the network as a whole, due to the user’s actions [6]. In Table I we have categorized several user-centric and network-centric objectives which a user may strive for by adapting transmit power. The following power allocation policy is presented with the intent of enabling a user to address both set of objectives. Subsequently, practical aspects governing closed-loop implementation of the algorithm shall be discussed.

A. Power Allocation Policy

A fundamental criterion in the determination of a user’s QoS is the attained SIR during communication. The $i$th user’s SIR error

$$e_i(k) = \gamma_i^\text{att} - \gamma_i(k)$$

may be viewed as a user-centric metric since it indicates the deviation between the user’s received SIR and target SIR $\gamma_i^\text{att}$. We propose that the $i$th user dynamically adapt transmit power so as to achieve

$$\min_{\rho_i} P_i(k+1) + \rho_2 e_i^2(k+1)$$

subject to $P_{i}^{\min} \leq P_i(k+1) \leq P_{i}^{\max}$ (13)

with the positive weights $\rho_1$ and $\rho_2$ dictating the priority given by user $i$ to controlling the level of network interference and the fulfillment of it’s SIR requirement, respectively. It will be shown shortly that, for a given user, it is only the ratio of the weights that is of relevance. Since constraints on transmit power must exist, the transmission power has been restricted to a maximum and minimum value of $P_{i}^{\max}$ and $P_{i}^{\min}$, respectively. The solution of the convex nonlinear optimization problem above can be obtained by application of the Karush-Kuhn-Tucker conditions [7]. It follows that the power update

$$P_i(k+1) = \begin{cases} 
P_i^{\min} & \text{if } I_i(k) > \frac{P_{i}^{\text{min}} - P_i(k)}{\alpha_i^*(k)}, \quad \alpha_i^*(k) < 0 \\
P_i^{\max} & \text{if } I_i(k) > \frac{P_{i}^{\text{max}} - P_i(k)}{\alpha_i^*(k)}, \quad \alpha_i^*(k) > 0 \\
I_i(k) + \alpha_i^*(k)I_i - \frac{\rho_2}{\rho_1} & \text{otherwise}
\end{cases}$$

(14)

(14)

with the gain

$$\alpha_i^*(k) = \arg \min \left\{ \frac{\rho_1 P_i^2(k+1)}{\alpha_i^*(k)} + \frac{\rho_2 e_i^2(k+1)}{\alpha_i^*(k)} \right\}$$

$$= \left[ P_i I_i^2(k+1) + \frac{\rho_2 e_i^2(k+1)}{\alpha_i^*(k)} + I_i(k) \gamma_i(k) \right] / \left[ I_i(k) G_{i}(k)(1 + \rho_1 I_i^2(k+1)) \right]$$

(15)

is the optimal policy for (13). In the derivation of $\alpha_i^*(k)$, the stochastic perturbations $\{g_{ij}\}$ were replaced with their mean values of zero. This was done under the presumption of a user not having channel state information (CSI) pertaining to the link gains of the other users, nor being capable of accurately tracking the small-scale effects of the channel during autonomous operation. As previously alluded to, the trade-off between the attainment of a user’s target SIR and interference reduction is controlled by the ratio

$$\rho_i = \frac{\rho_1}{\rho_2}.$$ 

The case of $\rho_i = 0$ denotes that the $i$th user may transmit at arbitrarily high power (subject to the power constraint) and dispense an unregulated amount of interference into the network in hope of meeting its target SIR. Such notion is supported by the absence of the aggregate interference $I_i(k)$ in the objective function when $\rho_i = 0$. It can be verified from (15) that in the extreme case of $\rho_i = \infty$ the $i$th user will transmit with minimum power regardless of its perceived interference $I_i(k)$. It is imperative to note that the computation of $\alpha_i^*(k)$ requires knowledge of the current (estimated), and the next-step (predicted) values of the perceived interference.

Distributed interference estimation will be discussed in the following subsection.

With the user-centric and network-centric concepts defined within the realm of power control, we conjecture that depending on the user’s application, a power control policy will follow one of two strategies:

- **Greedy approach**: Adaptation of transmit power in response to channel variation with the goal of maintaining a target SIR value. A user may be best suited to use such a strategy when having an application which has a continuous stream of delay sensitive traffic.

- **Energy efficient approach**: Opportunistic allocation of transmit power relative to the channel state. In other words, the user would increase transmit power for good channel conditions (i.e. low $I_i(k)$), decrease power for poor channel conditions, and transmit with minimal power once its channel quality falls below a certain
threshold. Such an approach is typically referred to as "water-filling" [8], and is beneficial to a user with an application which consists of bursty traffic which is delay insensitive.

The greedy approach leads to a user increasing transmit power when witnessing increasing levels of interference, whereas the energy efficient approach would see the user lowering power or possibly ceasing transmission. After all, the greedy user is continuously aiming for a target SIR, but is certainly not energy efficient in doing so. Conversely, an energy efficient user is willing to sacrifice instantaneous QoS by lowering transmit power during poor channel conditions and halting transmission after a cutoff point. Naturally, it would be advantageous for an energy efficient user to either decrease its transmission rate or increase forward error correction (FEC) when lowering transmit power during unfavorable channel states. With transmitter power being an indispensable commodity in reliable wireless communication, its regulation and the subsequent conservation of energy is imperative. From a user-centric perspective, energy efficiency is important in lessening power dissipation and prolonging the user’s battery life. From a network-centric perspective, energy efficiency reduces the aggregate network interference. This results in increased network capacity, admission of additional users, and prolonged lifetime of the network.

The presented power control policy was derived with the intent of enabling a user the capability to address user-centric and network-centric objectives via either an energy efficient or greedy approach to power allocation. An energy efficient user addresses its network-centric performance by regulating the amount of interference he introduces into the network, and addresses its user-centric performance by conserving transmit power. A greedy user is solely concerned with its user-centric performance and, with an assignment of $\rho_i = 0$, adapts transmit power so as to maintain a target SIR during communication. The presented power control policy allows a user to be either greedy or energy efficient through the assignment of $\rho_i$. This can be seen by examination of a user's power adaptation with respect to its perceived interference. From (15) we observe that the condition $\alpha_i^*(k) \leq 0$ in (14) can be alternatively expressed as $L_{-i}(k) \geq T_i(P_i(k))$ with

$$T_i(P_i(k)) \triangleq \frac{\sum_{j \neq i} L_{-j}(k+1) - P_i G_{ii}(k) + L_{-i}(k+1)}{\gamma_i(k)}.$$ 

As a result, the dynamics of a user’s power evolution as a function of perceived interference is illustrated in Fig. 2 with $P_i^{*}$ indicating a non-extremum power level, and $P_i^{\text{min}}$ ($P_i^{\text{max}}$) denoting the state at which the user transmits with minimum (maximum) allowable power. Interestingly, it is possible for a user to even waver between the greedy and energy-efficient approaches by adapting $\rho_i$ in correspondence with its application, traffic, or channel condition. Alternately, $\rho_i$ may be statically assigned to a user by the network for the duration of the user’s lifetime.

**B. Closed-loop Implementation**

The feedback provided to users via closed-loop power control is instrumental in the mitigation of small-scale fluctuations caused by multipath and user mobility. Attention is now focused on practical issues which must be addressed for closed-loop implementation of the power control policy presented above. As previously alluded to, in performing a power update
a user requires an estimate and next-step prediction of its perceived interference at the base station. Upon measurement of the feedback, the estimated and predicted interference values \( \hat{L}_i(k) \) and \( \hat{L}_i(k+1) \), respectively, can be computed as shown in Fig. 3 with \( K_i(k) \) denoting the estimator gain. Normality of the disturbances \( w_i(k) \) and \( v_i(k) \) would constitute the deployment of the Kalman filter for minimum mean square error (MMSE) estimation of the perceived interference. The MMSE estimation is contingent upon the user’s estimator having knowledge of the statistics of the disturbances. The measurement noise is locally impinging upon the received feedback of the \( i \)th user, and hence it’s statistics are assumed to be known a priori as \( v_i(k) \sim N(0, V_i(k)) \). Inspection of (8) reveals that the distribution of the driving disturbance may not be very instructive to derive since it is a function of parameters which are not locally known by the \( i \)th user. More specifically, an arbitrary user would not be aware of the transmit power of other users nor have statistical information pertaining to the stochastic link gains of the other transmitters. Thus, we focus on devising a method by which a user can autonomously obtain the statistics of it’s driving disturbance. With \( \{G_{ij}(k)\} \) and \( \{g_{ij}\} \) being Normal, we invoke a Gaussian assumption on (8) by assuming \( w_i(k) \sim N(b_i(k), Z_i(k)) \). Such presumed Normality also justifies the use of the Kalman filter for MMSE estimation. From the state equation in (11) it follows that \( b_i(k) = E[I_{i,k}(k+1) - I_{i,k}(k)] \). Therefore, we designate the sequences

\[
\hat{b}_i(k) = \frac{1}{K} \sum_{n=k-K+1}^{k} \hat{L}_i(n+1) - \hat{L}_i(n) \tag{16}
\]

and

\[
\hat{Z}_i(k) = \frac{1}{K} \sum_{n=k-K+1}^{k} [\hat{L}_i(n+1) - \hat{L}_i(n)]^2 - \hat{b}_i^2(k) \tag{17}
\]

as approximations to the maximum-likelihood (ML) estimates of the mean and variance of the driving disturbance \( w_i(k) \), respectively. The deviation between the two approximations above and the ML estimates is dependent upon the accuracy of the approximation \( I_{i,k}(k+1) - I_{i,k}(k) \neq I_{i,k}(k+1) - I_{i,k}(k) \). Accordingly, the Kalman filter used by the \( i \)th user is specified as

\[
\hat{I}_{i,k}(k+1) = \hat{I}_{i,k}(k) + C_i Q_i(k) \left( C_i^T Q_i(k) + V_i(k) \right)^{-1} (Y_i(k) - C_i \hat{L}_{i,k}(k)) \tag{18}
\]

with the corresponding Riccati equation given by

\[
Q_i(k+1) = Q_i(k) - C_i Q_i(k) \left( C_i^T Q_i(k) + V_i(k) \right)^{-1} C_i Q_i(k) + Z_i(k) \tag{19}
\]

and \( C_i \triangleq E[1 + c_i(k)] = 1 - P_{\text{loss}} \).

The decentralized nature of the algorithm is exemplified by the fact that, in performing a power update via (14), a user requires only local information pertaining to its perceived interference and the link gain to its intended receiver. The algorithm can be implemented locally at each user as shown in Fig. 1. Interestingly, we note that a user’s perceived interference is heavily dependent upon the dynamics of the interferers’ channels. Examination of (8) reveals that, for

\[
\alpha_j^*(k) = 0 \quad \forall \quad j \neq i, \quad \text{the driving disturbance would reduce to} \quad w_i(k) = \sum_{j \neq i} P_j(k) g_{ij} \cdot \text{Such a scenario would only be feasible if the interferers had deterministic channels characterized by deterministic link gains and no exogenous disturbances. In such a case, assuming feasibility of the target SIRs [2], the transmit powers would converge to fixed values at} \quad k^*, \quad \text{and thus for} \quad k \geq k^* \quad \text{we would have} \quad \alpha_j^*(k) = 0 \quad \forall \quad j \neq i. \quad \text{Hence, from the ith user’s perspective, the disturbance} \quad w_i(k) \quad \text{may be attributed in large part to the stochastic nature of the interferers’ channels}.

IV. SIMULATION RESULTS AND DISCUSSION

In this section the performance of the presented power control algorithm is evaluated via simulation. We consider the uplink of a single-cell CDMA system supporting 20 active users, with the extension to the multiple base station scenario being straightforward. The use of a linear receiver allows the \( i \)th user’s SIR to be defined as

\[
\gamma_i(k) = \frac{P_i(k) h_i [c_i^T(k) s_i(k)]^2}{\sum_{j \neq i} P_j(k) h_j [c_j^T(k) s_j(k)]^2 + c_i^T(k) c_i(k) \eta_i} \tag{20}
\]

with \( s_i(k) \in \mathbb{R}^L \) and \( c_i(k) \in \mathbb{R}^L \) denoting the user’s length \( L \) codeword and receive vector, respectively. The constant \( L \) denotes the processing gain, and the gains \( \{h_j\} \) represent the path-loss. The signature sequence \( s_i = [s_{i1}, s_{i2}, \ldots, s_{iL}]^T \) is fixed over the duration of the power control algorithm. All signature sequences will be generated randomly with \( s_{ij} \in \{-1, 1\} \), and a matched filter receiver (i.e., \( c_i(s) = s_i(s) \)) will be used for demodulation. Comparison of (20) with (1) reveals that the deterministic portion (or, in other words, the mean) of the link gains are represented as

\[
G_{ij} = \begin{cases} 
   h_i & \text{if} \quad i = j \\
   h_j (s_i^T s_j)^2 & \text{if} \quad i \neq j.
\end{cases} \tag{21}
\]

The random perturbations to (21) denoting the stochastic nature of the channel are modeled via (5) and assumed to have a variance of \( \text{Var}[\hat{G}_{ij}(k)] = G_{ij}/\mu_1 \) with \( 1 < \mu_1 \). Similarly, the sequence of random variables \( \{g_{ij}\} \) in (4) are assumed to have a variance of \( \text{Var}[g_{ij}] = G_{ij}/\mu_2 \) with \( 1 < \mu_2 \).

A frequently used path loss model for cellular radio is given by

\[
h_i = P_R \left( \frac{d_R}{d_i} \right)^n = \frac{A}{d_i^\mu} \tag{22}
\]
where $d_R$ is a reference distance, $P_R$ is the received power at the reference distance, $d_i$ is the distance between the base station and the $i$th user, and $n$ denotes the path loss exponent. We shall assume a path loss exponent of $n = 4$ and assign $A = 10^{-4}$ in correspondence to a path gain of $-40$ dB at a reference distance of 1 km with a 1.9 GHz carrier frequency [9]. A single circular cell with a coverage range of radius $r = 1$ km will be assumed, along with a background noise power of $\eta_i = 10^{-3}$ mW at the intended receiver of each user. Within the cell, the users’ locations will be generated uniformly on the interval of $[0, r]$. A processing gain of $L = 128$ will be allocated to each user along with a maximum power level of $P_{i_{\text{max}}} = 500$ mW. Initially each user shall be assigned the minimum allowable power of $P_{i_{\text{min}}} = 0.0$ mW. With respect to the feedback channel from the base station to each user, the variance of the measurement noise will be specified as $\xi_i(k) = 10^{-3}$ mW, and a feedback loss probability of $P_{i_{\text{loss}}} = 0.05$ shall be assumed. A window size of $K = 200$ samples will be used in empirically obtaining the statistics of the driving disturbance via (16) and (17). With the empirical system outlined above, we first examine the performance of the distributed power control algorithm within the stochastic setting. Subsequently, the utility of the policy shall be examined within the context of enabling a user to jointly address user-centric and network-centric objectives.

The power and SIR evolution of each user is shown in Fig. 4 for $\mu_1 = \mu_2 = 10$. All users were designated as being greedy via the assignment $p_1 = p_2 = \ldots = p_{20} = 0$, and each user had a target SIR of $\gamma_{i_{\text{tar}}} = 5$. Satisfactory performance is observed with respect to the SIR of all users being at, or sufficiently close to, the target value. The stochastic convergence of the transmit powers, as defined by $|\alpha_i^*(k)| \leq 0.01 \forall i$, is seen after approximately 90 iterations. It is imperative to note that each user was able to obtain such performance in autonomous fashion, with partially observable feedback, and without a priori knowledge pertaining to the statistics of the disturbances.

We now investigate the dynamics of the algorithm as far as enabling a user to address user-centric and network-centric objectives by adopting either a greedy or energy efficient approach to power control. For lucidity in presentation we ignore the random channel detriments and restrict attention to a deterministic setting. This is because, in contrast to the simulation above, we wish to specifically examine the dynamics of the algorithm rather than its robustness to stochastic impairments. Hence, in the forthcoming simulation, each user’s feedback shall be noiseless and the link gains shall be deterministic with no stochastic perturbations to (21). The power and SIR evolution of the 20 users is shown in Fig. 5 with each user adapting power in a greedy fashion for the first one-hundred power updates via the assignment $p_i = 0 \forall i$. Due to the feasibility of the target SIRs [2], all users attain their target SIR value upon convergence of the transmit powers. In fact, the converged power and SIR values of the users correspond to those obtained with classical greedy algorithms such as [1]. The two users dissipating the most power (users with indices 3 and 8) autonomously choose to be energy efficient by selecting $p_3 = 10$ and $p_8 = 10$ for $100 < k \leq 200$. A resultant savings of 27 percent and 47 percent in transmission power is witnessed by user 3 and 8, respectively. Within the user-centric paradigm, the two users are sacrificing instantaneous SIR in favor of power conservation and prolonged battery life. A more subtle occurrence is the collective power conservation of the greedy users which comes at no sacrifice to their QoS. Specifically, a mean power savings of 17 percent is experienced by the 18 greedy users. This is due to users 3 and 8 addressing their network-centric objectives of decreasing the interference which they introduce into the network, and reducing the power dissipation of the other network users. We make the following point in retrospect to users 3 and 8 achieving below-target SIR values during the interval $100 <$
An energy efficient user witnessing degraded SIR performance via $\gamma(k) < \gamma_{min}$ may still fulfill an application-specific bit error rate (BER) requirement. However, this would come at a sacrifice in delay since the user would either require excessive retransmissions, or increased FEC to compensate for its degraded SIR. Thus, further justifying the utility of the opportunistic energy efficient approach for applications with bursty and delay-insensitive traffic. Lastly, user 3 decides to further address energy efficiency via an assignment of $P_{3} = 0$ mW. As illustrated in Fig. 2, user 3 will only commence transmission in response to an improved channel state, or equivalently, a sufficiently smaller value of $I_{-3}(k)$ for $k > 300$. In response to the increased network-centric performance of user 3, an additional mean power saving of 23 percent is witnessed by the 19 transmitting users at no loss to their SIR performance. In addition to addressing network-centric objectives, user 3 may seek to optimize its throughput by resuming transmission with a higher data rate during a favorable channel state, after having remained dormant during such an unfavorable channel state.

V. CONCLUSION

A distributed stochastic power control policy has been presented for time varying wireless networks with partially observable feedback. Realistic degradations to the feedback channel were dynamically modeled, and the radio links were represented as stochastic processes. A critical feature of the algorithm is the capability of a user to allocate power so as to address various user-centric and network-centric objectives by being either greedy or energy efficient. It was observed that an energy efficient user shall adapt power so as to address user-centric and network-centric objectives; while a greedy user will solely address user-centric objectives. Subsequently, closed-loop implementation of the distributed algorithm with autonomous interference estimation was proposed. The versatility of the power control policy was shown via simulation, with users adapting transmit power in either greedy or energy efficient manner. Simulation results demonstrate superb performance with respect to robustness to stochastic detriments caused by small-scale variations of the wireless channel.

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