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# Joint Adaptive Distributed Rate and Power Control for Wireless Networks

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**Abstract**—A novel adaptive distributed rate and power control (ADRPC) protocol is introduced for wireless networks. The proposed controller contrasts from others by providing nonlinear compensation to the problem of transmission power and bit-rate adaptation. The protocol provides control of both signal-to-interference ratio (SIR) and quality-of-service (QoS) support to bit-rate adaptation. Bit-rate adaptation is performed by local estimation of congestion levels, rendering little packet overhead, using Lyapunov based adaptive control methods. Performance of the proposed control scheme is shown through analytical proof and simulation examples.

**Index Terms**—Weight-adaptation, Quality-of-Service, Lyapunov, Adaptive Control, Rate adaptation, Power Control

## I. INTRODUCTION

In wireless networking applications, the quality of service (QoS) issues are inter-related to channel dynamics and are important to network performance. To ensure QoS over a wireless channel for a particular bandwidth capacity, the transmission power and bit-rate must be controlled [1]. In many applications of wireless sensor networks (WSN) and ad-hoc networks increasing energy-efficiency while maintaining QoS is desirable. In these networks, distributed control methods providing analytically guaranteed performance that requires little overhead are desirable. In this paper, joint control of bit-rate and transmission power using a Lyapunov based decentralized adaptive controller is proposed.

Transmission power control provides reduction of power consumption, minimizes mutual interference, and provides maintenance of link capacity. Interference management at each node allows signal-to-interference ratio (SIR) to be satisfied for a specified data rate. Previously, rigorous work involving distributed power control (DPC) was performed for cellular networks [2-5]. Also, several DPC schemes [2, 4] were developed for wireless ad-hoc networks where the topology is dynamic due to node mobility and link failures.

Unlike wired networks, radio channel uncertainties in a wireless network, such as path loss, shadowing, and Rayleigh

fading, can attenuate the power of the transmitted signal causing variations in the SIR and degrading performance. Low SIR levels result in higher bit error rates (BER), causing increased numbers of dropped bits and/or packets. Many DPC schemes [2, 4] for ad hoc networks assume that: i) only path loss is present, ii) no other channel uncertainty exists, and iii) the mutual interference among the users is held constant during users' power updates. Currently there is previous work into methods that account for channel uncertainties for power control by Zawodniok et. al.[5].

In contrast, this work proposes a Lyapunov based method for joint control of bit-rate and transmission power, known as the distributed or decentralized rate and power control (ADRPC) protocol. Joint control of bit-rate and transmission power provides QoS assurances to overcome channel uncertainties and congestion levels. Application of adaptive control methods to analytically guarantee performance of both the bit-rate and power control and overcome limitations in previous works are presented. Additionally, desired SIR levels are chosen based on the desired bit-rate via Shannon's Capacity formula assuring sufficient channel capacity for generated traffic. The joint control method provides innovation in the form of a closed loop controller for the SIR and the bit-rate to meet user defined QoS while compensating for variations in channel state and network congestion.

## II. ADAPTIVE CONTROLLER METHODOLOGY

Adaptive estimation of the channel state and the network congestion facilitate control of bit-rate and transmission power. In this section a description of desired bit-rate selection based on user QoS is presented. Additionally, the impact of the bit-rates on the transmission power control for selection of the desired SIR level is discussed. Next, the bit-rate and SIR dynamics are presented with controller methodologies. Finally, controller performance is demonstrated through analytical proof of the stability of the proposed controller.

### A. Desired Rate Selection

To ensure proper QoS desired bit-rates should be chosen based on users' perceptions of how the network should perform for a given application. In this work the QoS metric is determined by the time a user specifies to send a payload of

data, or the end-to-end (E2E) delay. Desired bit-rates are calculated and updated for each time interval to account for received and dropped bits. Calculation of the bit-rate over the first time interval is given by the total number of bits for transmission divided by the E2E-delay requirement. At each subsequent time interval, the desired bit-rate is updated by calculation of the number of bits left for transmission and the time remaining for delivery. Desired bit-rates at each time interval for the  $i^{\text{th}}$  node are selected as

$$r_{des,i}(l) = \chi_i(l) / t_{f,i} \quad (1)$$

where the number of bits to send is given by  $\chi_i(l)$ , and  $t_{f,i}$  is the time remaining for the transmission. Desired bit-rates are then updated at each time interval to accommodate the QoS and account for any dropped bits or lags in the rate due to other variables. It should be noted, in this work the desired rate selection is not made to be complex since the main contribution is the bit-rate and power control. More sophisticated rate control methods could be used in place of (1) using the same control architecture.

#### B. Radio Channel with Uncertainties

Radio channels place fundamental limitations on wireless communication systems. The transmission path can vary from line-of-sight (LOS) to a path obstructed by buildings, mountains, and foliage. In wireless networks, channel uncertainties such as path loss, shadowing, and Rayleigh fading attenuates signal power and introduces variations in the SIR at the receiver degrading performance of DPC schemes. The effect of these uncertainties is represented through a channel loss (gain) factor that typically multiplies with the transmitter power. Therefore, the channel loss or gain,  $g$ , can be expressed as

$$g = f(d, n, X, \zeta) = d^{-n} \cdot 10^{0.1\zeta} \cdot X^2 \quad (2)$$

where  $d^{-n}$  is the effect of path loss due to the distance,  $d$ , and the  $10^{0.1\zeta}$  term corresponds to the effect of shadowing [12]. For Rayleigh fading, it is typical to model the power attenuation as  $X^2$ , where  $X$  is a random variable with Rayleigh distribution.

#### C. Desired SIR Selection

The desired SIR at each time interval is based on the actual bit-rate that is being produced at each node ensuring that the SIR requirements at the nodes are satisfied. In contrast, desired SIR levels could be selected to satisfy the desired bit-rate, however this leads to cases where the transmission power is greater than needed when a desired bit-rate is not reached, and introduces additional interference. The desired SIR is based on Shannon's capacity formulation and is given by

$$\left[ SIR_{des,i}(l) \right]_{dB} = E_b / N_o + 10 \log_{10} (rate_i(l) / BW) \quad (3)$$

where the bandwidth efficiency,  $E_b / N_o$ , is chosen based on the desired bit-error-rate (BER) and modulation scheme. The desired bandwidth efficiency can be calculated or found in tables [13].

#### D. Adaptive Controller Formulation

Transfer of payload is controlled through the bit-rate adaptation by estimation of congestion levels in the network and user QoS metrics as described. The development of a Lyapunov based nonlinear adaptive control of transmission rate and power is also shown. First, the rate dynamics and the bit-rate control method are given by representing the network as an affine nonlinear discrete-time system. Next, the SIR dynamics and the associated control method are described. Finally, a unified control scheme is presented and is shown to be asymptotically stable for ideal conditions and to have bounded error in the presence of disturbances.

#### E. Rate Dynamics and Control

Bit-rate impacts the QoS and the congestion level of a wireless network. Distributed control of the bit-rate and estimation of the congestion level is facilitated through adaptive methods. Bit-rate dynamics are used as proposed in [11] and are given as

$$r_i(k+1) = r_i(k) \Phi_i(k) + \mu d_i(k) \quad (4)$$

where  $\mu$  is a positive step-size,  $c_i(l)$  is the congestion level, and  $\Phi_i(l) = [1 - \mu c_i(l)]$ . In [11], the term  $d_i(l)$  is the bit-rate control input and is assumed to be a random variable with mean  $m_d$  and variance  $\sigma_d^2$ . In contrast, the proposed method provides control of the bit-rate via  $d_i(l)$  in conjunction with the transmission power levels,  $p_i(l)$ , to control the SIR and bit-rates simultaneously.

The error dynamics for the transmission rate control subsystem are given as

$$e_{r,i}(l) = r_i(l) - r_{des}(l) \quad (5)$$

and the error in the next time step can be shown as

$$e_{r,i}(l+1) = r_i(l) \Phi_i(l) + \mu d_i(l) - r_{des}(l+1) \quad (6)$$

Introducing the control law of

$$d_i(l+1) = (1/\mu) \left[ k_r e_r(l) + r_{des}(l+1) - r_i(l) \hat{\Phi}_i(l) \right] \quad (7)$$

where  $\hat{\Phi}_i(l)$  is an unknown bounded parameter vector to be estimated due to congestion level, which is typically unknown. Using the error dynamics given in (6) and the control law in (7) the resulting error dynamics for the bit-rate are given by

$$e_{r,i}(l+1) = r_i(l) \tilde{\Phi}_i(l) + k_r e_r(l) \quad (8)$$

where  $\tilde{\Phi}_i(l)$  is the parameter estimation error for the rate control. With the addition of a parameter estimation error term that is given as  $\mathcal{E}_r(l)$ , which is considered bounded as

$$\|\mathcal{E}_r(l)\| \leq \mathcal{E}_{r,\max} \text{ where } \mathcal{E}_{r,\max} \text{ is a known constant.}$$

Next, two cases for control are shown. In the first case, an asymptotically stable system is demonstrated in ideal situations whereas in the second case boundedness can be shown in the presence of bounded estimation errors without the persistency of excitation (PE) condition.

**Case 1:**  $\Phi_i$  and  $B_i(l)$  are known. In this scenario, the feedback bit-rate control is selected as

$$u_i(l) = B_i^{-1} [k_r e_{r,i}(l) + r_{des,i}(l) - \Phi_i(l) r_i(l)] \quad (9)$$

where the error in the states is defined as in (5) and  $B_i = \mu$ .

The resulting error dynamics are given as

$$e_{r,i}(l+1) = k_r e_{r,i}(l) \quad (10)$$

With appropriate selection of  $k_r$ , the Eigenvalues are placed within the unit disc; it is easy to show that the closed-loop system is asymptotically stable in the mean as given in Theorem 1.

**Case 2:**  $\Phi_i$  and  $B_i(l)$  are unknown. In this scenario, equation (4) can be expressed as

$$r_i(l+1) = \Phi_i(l) r_i(l) + B_i(l) u_i(l) \quad (11)$$

Selecting the feedback control as (6), where  $\hat{\Phi}_i(l)$  is the estimate of  $\Phi_i(l)$ , the state error system is expressed as

$$e_{r,i}(l+1) = k_r e_{r,i}(l) + \tilde{\Phi}_i^T(l) r_i(l) + \varepsilon(l) \quad (12)$$

where  $\tilde{\Phi}_i(l) = \Phi_i(l) - \hat{\Phi}_i(l)$  is the parameter estimation error.

In this case, a standard adaptive parameter update law is chosen as

$$\hat{\Phi}_i(l+1) = \hat{\Phi}_i(l) + \sigma \psi_i(l) e_{r,i}^T(l+1) \quad (13)$$

where  $\psi_i(l) = r_i(l)$ .

**Theorem 1:** Given the rate dynamics above with uncertain levels of congestion, if the feedback bit-rate control is selected as (7), then the congestion estimation error along with the mean rate error converges to zero asymptotically, if the parameter updates are taken as (13) provided

$$\sigma \|\psi_i(l)\|^2 < 1 \quad (14)$$

$$k_{v,max} < 1/\sqrt{\delta} \quad (15)$$

where  $\delta = 1/(1 - \sigma \|\psi_i(l)\|^2)$ , and  $\sigma$  is the adaptation gain. A full version of this proof can be found in [14].

From (8), it is clear that the closed-loop error system is the network congestion estimation error. If the congestion levels are properly estimated, then estimation error tends to be zero. In this case, equation (8) becomes (10). In the presence of error in estimation, only boundedness of error can be shown similar to the case of adaptive power control (see next section where similar results are shown for joint power and rate control). We can show that the rates approach close to the target provided the system uncertainties are properly estimated. Additionally, in this case the parameter update will only converge close to the actual values under the assumption of persistently excitation (PE) of the inputs. Since the PE condition is difficult to guarantee over all time it will be relaxed in the joint controller framework presented later in this work by modification of the parameter update law.

#### F. SIR Dynamics and Control

Control of the transmission power impacts the SIR at all

other nodes. Distributed control provides estimates of channel conditions through adaptive methods are introduced in this section. The goal of transmitter power control is to maintain a target SIR threshold for each wireless link through adjustment of transmitter power meeting capacity requirements and preserve energy. In this section the dynamics of the SIR system are presented.

Suppose there are  $N \in Z_+$  links in the network. Let  $g_{ij}$  be the power loss (gain) from the transmitter of the  $j^{th}$  link to the receiver of the  $i^{th}$  link. The power attenuation is considered to follow the relationship given in equation (2).

Calculation of SIR,  $R_i(t)$ , at the receiver of  $i^{th}$  link at the time instant  $t$ , is given by

$$R_i(t) = \frac{g_{ii}(t) P_i(t)}{I_i(t)} = g_{ii}(t) P_i(t) / \left( \sum_{j \neq i} g_{ij}(t) P_j(t) + \eta_i(t) \right) \quad (16)$$

where  $i, j \in \{1, 2, 3, \dots, n\}$ ,  $I_i(t)$  is the interference,  $P_i(t)$  is the link's transmitter power,  $P_j(t)$  are the transmitter powers of all other nodes, and  $\eta_i(t) > 0$  is the variance of the noise at its receiver node. Now the dynamic system is presented in (17), for a full treatment of the SIR dynamics see [5].

The dynamics of the SIR are given in (17) where  $\omega(l)$  is the zero mean stationary stochastic channel noise with  $n_i(l)$  as its coefficient. The SIR of each link at time instant  $l$  is obtained as

$$y_i(l+1) = \alpha_i(l) y_i(l) + \beta_i(l) v_i(l) + n_i(l) \omega_i(l) \quad (17)$$

Carefully observing (17), it is clear that the SIR at the time instant  $l+1$  is a function of channel variations,  $\alpha_i(l)$ , from time instant  $l$  to  $l+1$ . The channel variation is not known a priori, making the DPC scheme development challenging. Since  $\alpha_i(l)$  is not known, it must be estimated for the development of DPC methods. Equation (17) can be rewritten as

$$y_i(l+1) = \tau_i^T(l) \gamma_i(l) + \beta_i(l) v_i(l) \quad (18)$$

where the regression vector  $\gamma_i(l) = [y_i(l) \ \omega_i(l)]$  and the

unknowns are  $\tau_i^T(l) = [\alpha_i(l) \ n_i(l)]$  and

$$\alpha_i(l) = [\Delta g_{ii}(l) / g_{ii}(l)] - \quad (19)$$

$$\left[ \left( \sum_{j \neq i} \Delta g_{ij}(l) P_j(l) + \Delta P_j(l) g_{ij}(l) \right) / (I_i(l)) \right]$$

and

$$\beta_i(l) = g_{ii}(l) \quad (20)$$

The control input can be selected as (21) and

$$v_i(l) = P_i(l+1) / I_i(l) \quad (21)$$

**Remark:** The control of the SIR is similar to the case of previously presented rate control. Therefore the SIR control can similarly be shown to be asymptotically stable and bounded with removal of the PE condition. Due to PE condition being difficult to guarantee the PE condition will be relaxed in the next section when the joint controller framework is proposed and proofs are given.

### G. Joint Controller

Using the system dynamics described above a joint control system is now proposed. The two control systems are concatenated to form a single state-space system and then control methods are applied. The connection between rate and SIR is not presented in the proof to allow different methods for calculation of desired SIR levels from the bit-rate. Additionally, as long as the employed relationship between the rate and SIR will provide provides stable inputs to the inter-system stability will be preserved. A rigorous treatment of the stability and performance is shown. The proofs reflect the performance of the control methods in an ideal environment and in a non-ideal setting with estimation errors. When estimation errors are present, the control method can be shown to have a bounded error. Rewrite (11) and (18) as

$$x_i(l+1) = \theta_i(l)x_i(l) + B(l)u(l) \quad (22)$$

where  $x_i(l+1) = [r_i(l+1) \ y_i(l+1)]^T$ ,

$$\theta_i(l) = \text{diag}\{\Phi_i(l) \ \tau_i(l)\}, \text{ and } x_i(l) = [r_i(l) \ y_i(l)]^T.$$

The control input is given as

$$u_i(l+1) = B_i^{-1} [K_{v,i}e(l) + x_{d,i}(l+1) - \hat{\theta}_i(l)x_i(l)] \quad (23)$$

which yields the joint power and bit-error dynamics as

$$e_i(l+1) = K_{v,i}e(l) + \tilde{\theta}_i^T(l)x_i(l) + \varepsilon(l) \quad (24)$$

The ADRPC method is now shown for the case when both  $\theta_i(l)$  and  $B_i(l)$  are unknown. For implementation the parameter  $\beta_i$  is calculated using (20) as ratio between received and transmitted signal strength and the parameter  $\mu$  is user defined [5]. The control method is shown to have mean estimation error along with the mean state error that is bounded. The cases where both  $\theta_i(l)$  and  $B_i(l)$  are known are similar to proofs presented earlier in the rate control methods. In this section, an update method for the adaptive estimation is presented that allows for relaxation of the PE condition providing stable bounded estimations and control in the mean.

When  $\theta_i(l)$  and  $B_i(l)$  are unknown, equation (22) can be expressed as an affine nonlinear discrete-time system

$$x_i(l+1) = \theta_i(l)x_i(l) + B_i(l)u_i(l) \quad (25)$$

Now selecting feedback control as

$$u_i(l+1) = B_i^{-1} [K_{v,i}e(l) + x_{d,i}(l+1) - \hat{\theta}_i(l)x_i(l)] \quad (26)$$

where  $\hat{\theta}_i(l)$  is the estimate of  $\theta_i(l)$ . Then the state error system is expressed as

$$e_i(l+1) = K_{v,i}e(l) + \tilde{\theta}_i^T(l)x_i(l) + \varepsilon(l) \quad (27)$$

where  $\tilde{\theta}_i(l) = \theta_i(l) - \hat{\theta}_i(l)$  is the parameter estimation error. From (27), it is clear that the closed-loop error dynamics are driven by channel estimation and the network congestion estimation errors. If the channel uncertainties and congestion levels are properly estimated, then estimation error tends to be zero. In the presence of error in estimation, only boundedness

of error in can be shown. We can show that the actual system states approach the target provided the system uncertainties are properly estimated. To proceed further, the Assumption 1 is used as in [5].

**Assumption 1:** The channel and congestion levels change slowly in comparison to parameter updates.

**Remark:** The above assumption is standard in the adaptive control literature. A safety factor is included to compensate for both sudden changes in the SIR and the congestion of the network.

Consider now the closed-loop error dynamics with parameter estimation error,  $\varepsilon(l)$ , as

$$e_i(l+1) = K_{v,i}e_i(l) + \tilde{\theta}_i^T(l) \cdot \psi_i(l) + \varepsilon(l) \quad (28)$$

where  $\varepsilon(l)$  is considered bounded above  $\|\varepsilon(l)\| \leq \varepsilon_N$ , with  $\varepsilon_N$  a known constant. It is typical in the standard adaptive control [15] to assume the estimation errors to be zero and demonstrating stability by applying certainty equivalence principle. By contrast, in this work, the estimation errors are not considered as zero and certainty equivalence principle is relaxed.

**Theorem 2:** Given the adaptive scheme above with channel and congestions uncertainties for a wireless network, if the feedback from the scheme is selected as (27), then the mean estimation and state errors are bounded, if the parameter updates are taken as

$$\hat{\theta}_i(l+1) = \hat{\theta}_i(l) + \sigma \psi_i(l) e_i^T(l+1) - \Gamma \|I - \sigma \psi_i^T(l) \psi_i(l)\| \hat{\theta}_i(l) \quad (29)$$

where  $\Gamma > 0$  is a design parameter, and  $\psi_i(l) = x_i(l)$ , where  $\psi_i(l)$  is formally known as the regression matrix and is simply the states for our purposes. Then the mean error in states  $e_i(l)$  and the mean estimated channel and congestion parameters,  $\hat{\theta}_i(l)$ , are bounded without the need for the PE condition, with the bounds specifically given by (38) and (40) provided

$$\sigma \|\psi_i(l)\|^2 < 1 \quad (30)$$

$$0 < \Gamma < 1 \quad (31)$$

$$K_{v,i,\max} < 1 / \sqrt{\delta} \quad (32)$$

where

$$\delta = \eta +$$

$$1 / \left( \left( 1 - \sigma \|\psi_i(l)\|^2 \right) \left[ \Gamma^2 \left( 1 - \sigma \|\psi_i(l)\|^2 \right)^2 \right. \right. \quad (33)$$

$$\left. \left. + 2\sigma \Gamma \|\psi_i(l)\|^2 \left( 1 - \sigma \|\psi_i(l)\|^2 \right) \right] \right)$$

and  $\sigma$  is the adaptation gain.

**Note:** The parameters  $\sigma$ ,  $\eta$ ,  $\delta$  are dependent upon the desired SIR and bit-rate values with time.

**Proof:** Select a Lyapunov function candidate as

$$J_i = e_i^T(l) e_i(l) + \frac{1}{\sigma} \kappa [\tilde{\theta}_i^T(l) \tilde{\theta}_i(l)] \quad (34)$$

Using the estimation error shown in (28) and parameter tuning mechanism (29) to obtain

$$\begin{aligned} \Delta J \leq & -\left[1 - \sigma K_{v,j,\max}^2\right] \|e_i(t)\|^2 - \\ & \left[1 - \sigma \Psi_i^T(t) \Psi_i(t)\right] \|\tilde{\theta}_i^T(t) \Psi_i(t) - \\ & \frac{1}{(1 - \sigma \Psi_i^T(t) \Psi_i(t))} \left( \sigma \Psi_i^T(t) \Psi_i(t) + 2\Gamma \right) \left\| I - \sigma \Psi_i(t) \Psi_i^T(t) \right\| \\ & \cdot \left( K_{v,j} e_i(t) + \varepsilon(t) + d(t) \right) \|^2 + \\ & 2\gamma K_{v,j,\max} \|e_i(t)\| + \rho \\ & - \frac{1}{\sigma} \left\| I - \sigma \Psi_i(t) \Psi_i^T(t) \right\|^2 \left[ \Gamma(2 - \Gamma) \|\hat{\theta}_i(k)\| \theta_{\max} - \Gamma^2 \theta_{\max}^2 \right] \end{aligned} \quad (35)$$

where

$$\gamma = \left[ \eta(\varepsilon_N + d_M) + \Gamma(1 - \sigma \|\Psi_i(t)\|^2) \|\Psi_i(t)\| \theta_{\max} \right] \quad (36)$$

and

$$\rho = \left[ \begin{array}{l} \eta(\varepsilon_N + d_M)^2 + \\ 2\Gamma(1 - \sigma \|\Psi_i(t)\|^2) \|\Psi_i(t)\| \theta_{\max} (\varepsilon_N + d_M) \end{array} \right] \quad (37)$$

Completing the squares for  $\tilde{\theta}_i(t)$  in (35) and taking the expectation of both sides results in  $E(J) > 0$  and  $E(\Delta J) \leq 0$ , this shows the stability in the mean via sense of Lyapunov provided the conditions (30) and (32) hold. This demonstrates that  $E(\Delta J)$  is negative outside a compact set  $U$ . According to a standard Lyapunov extension, the state error  $E[e_i(t)]$  is bounded for all  $t \geq 0$  and the upper bound on the mean state error is given by

$$E(\|e_i(t)\|) > \frac{1}{(1 - \sigma K_{v,j,\max}^2)} \left[ \gamma K_{v,j,\max} + \sqrt{\rho_1 (1 - \sigma K_{v,j,\max}^2)} \right] \quad (38)$$

where

$$\rho_1 = \rho + \frac{1}{\sigma} \frac{\Gamma}{2 - \Gamma} (1 - \sigma \|\theta(t)\|^2) \theta_{\max}^2 \quad (39)$$

On the other hand, completing the squares for  $\|\tilde{\theta}_i(t)\|$  in (35) results in  $E(\Delta J) \leq 0$  as long as the conditions (30)-(32) are satisfied and

$$E(\|\tilde{\theta}_i(t)\|) > \left( \frac{\Gamma(1 - \Gamma) \theta_{\max}}{\sqrt{\Gamma^2(1 - \Gamma)^2 \theta_{\max}^2 + \Gamma(2 - \Gamma) \Theta}} \right) / (\Gamma(2 - \Gamma)) \quad (40)$$

where

$$\Theta = \left[ \Gamma^2 \theta_{\max}^2 + \sigma \rho_1 / (1 - \sigma \|\Psi_i(t)\|^2) \right] \quad (41)$$

and

$$\rho_1 = \rho + (\gamma^2 k_{v,\max}^2 / (1 - \delta k_{v,\max}^2)) \quad (42)$$

In general  $E(\Delta J) \leq 0$  in a compact set as long as (30) and (33) are satisfied and either (38) or (40) hold. According to the standard Lyapunov extension theorem [15], this demonstrates that the tracking error and the error in parameter estimates are bounded.

#### Remarks:

a) For practical purposes, (38) and (40) can be considered as bounds for  $\|e_i(t)\|$  and  $\|\tilde{\theta}_i(t)\|$ .

b) Parameter reconstruction error bound  $\varepsilon_N$  and the

bounded channel disturbances  $d_M$  increase the bounds on  $\|e_i(t)\|$  and  $\|\tilde{\theta}_i(t)\|$  in a very interesting way.

c) Lyapunov proofs for nonlinear discrete-time systems are relatively difficult to pursue when compared to continuous-time since the first difference of the Lyapunov function is quadratic with respect to the states whereas it is linear in the case of continuous-time. This makes the proof quite complicated and challenging whereas it is still accomplished in this work.

### III. RESULTS AND DISCUSSION

Simulations were carried out for random topologies with over a 50 by 50 m<sup>2</sup> area to evaluate the performance of the controller as placement, density, and congestion vary. Results for representative performance are now presented.

To highlight the ability of the adaptive controller to estimate congestion levels initial simulations were performed. A triangular pulse with a mean random noise was input as a congestion level; congestion levels and estimated values are shown in Fig. 1. Figure 1 shows the method is capable of estimation and can compensate for network congestion.

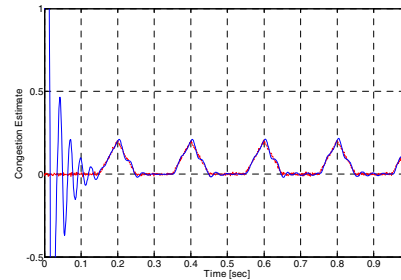


Fig. 1 Results of congestion estimation

A dynamic channel as described in (2) was used for simulation. The channel is assumed to vary slower than the update of the controller system. For each simulation a random channel state over time is generated so each run must overcome a unique channel pattern. Results show that the joint adaptive controller is capable of meeting QoS requirements as proposed in previous sections. The ADRPC was simulated in MATLAB<sup>®</sup> with a dynamic channel, a probabilistic bit drop-rate, and with varying numbers of nodes in random topologies.

Results for the ADRPC show the capability of controlling the bit-rate and SIR for each link. Both controllers provide suitable QoS by providing a desired bit-rate based on user defined time of arrival. In Fig. 2, the SIR is held higher to accommodate traffic flow during transfer and next falls to conserve power. Figure 3 depicts the controlled and desired bit-rates for the ADRPC. The ADRPC method provides suitable control and delivers the desired payload in the time period set by the QoS.

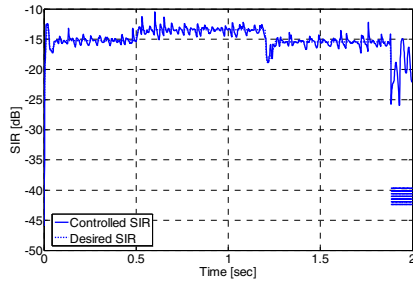


Fig. 2 ADRPC SIR levels

It is also observed that the power levels change to compensate for the channel gain; however, they do not stay at a higher level for long periods of time. Thus, the total energy expended to transmit data is minimized allowing for management of the channel capacity while simultaneously conserving energy over the lifetime of the wireless device. Figure 4 displays a representative example of the power levels found in simulation.

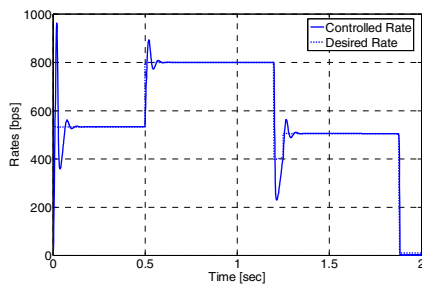


Fig. 3 ADRPC rates.

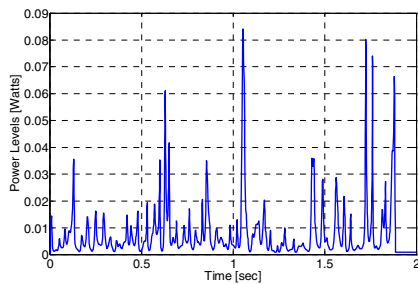


Fig. 4 Power levels

#### IV. CONCLUSIONS

In this paper a novel adaptive controller and an optimal tracking controller for the joint control of bit-rate and transmission power for wireless networks are introduced. The adaptive controller approach uses Lyapunov based stability analysis to provide analytically guaranteed convergence of the estimated parameters and asymptotic stability in terms of the error. The combined bit-rate and power control provide a

novel method for controlling the actual capacity of the channel for the current bit-rate being produced. By mathematically guaranteeing the channel capacity and estimating both the channel state and the congestion level in a distributed manner provide a robust protocol with little overhead. Results from simulation show that the control method presented provides adequate control with a minimal overhead. Analysis of the simulations reveals that the control methods perform well under dynamic channel conditions and with network congestion. Finally, QoS is enhanced since the bit-rates are set by user perceived metrics and these are met by the controller through tracking a desired rate trajectory allowing for greater network flexibility and performance.

#### REFERENCES

- [1] E. Babulak, "User perception of quality of service provision," *Proc. of the IEEE Int. Conf. on Industrial Technology*, vol. 2, pp. 1022-1025, 2003.
- [2] J. Gomez, A.T.Campbell, M.Naghshineh, and C.Bisdikian, "Conserving Transmission Power in Wireless Ad Hoc Networks," *Proc. of the IEEE Int. Conf. on Network Protocols (ICNP)*, pp. 24-34, 2001.
- [3] P. Karn, "MACA - A new channel access method for packet radio," *Proc. ARRL Computer Networking Conf.*, pp. 134-140, 1990.
- [4] M.B.Pursley, H.B. Russell, and J.S.Wysocarski, "Energy efficient transmission and routing protocols for wireless multiple-hop networks and spread-spectrum radios," *Proc. of the IEEE/AFCEA Conf. on Information Systems for Enhanced Public Safety and Security (EUROCOMM)*, Munich, Germany, pp. 1-5, 2000.
- [5] M. Zawodniok and S. Jagannathan, "A distributed power control MAC protocol for wireless ad-hoc networks," *Proc. of the IEEE Conf. on Wireless Communications and Network Conference (WCNC)*, vol. 3 pp. 1915-1920, 2004.
- [6] L. T. Ong, A. Olfat, and M. Shikh-Habaei, "Joint SNR target and rate adaptation based on bit error rate estimation," *Proc. of Int. Symp. on Wireless Communication Systems*, pp. 470-474, 2005.
- [7] A. K. Karmokar, D. V Djonin, and V. K. Bhargava, "Delay constrained rate and power adaptation over correlated fading channels," *Proc. of the IEEE Global Communications Conf. (GLOBECOM)*, vol. 6, pp. 3448-3453, 2004.
- [8] C-H. Jiang, and J-K. Lain, "Adaptive neuro-fuzzy power control and rate adaptation for multirate CDMA radio systems," *Proc. of the IEEE Int. Conf. on Networking, Sensing, and Control*, pp. 1307-1312, 2004.
- [9] M. Shikh-Bahaei, M. Mouna-Kingue, and G. Charbit, "Joint optimisation of outer-loop power control and rate adaptation over fading channels," *Proc. of the IEEE Vehicular Technology Conf. (VTC-Fall)*, vol. 3, pp. 2205-2209, 2004.
- [10] S. A. Jafar, and A. Goldsmith, "Optimal rate and power adaptation for multirate CDMA," *Proc. of the IEEE Vehicular Technology Conf. (VTS-Fall)*, Boston, MA, vol. 3, pp. 994-1000, 2000.
- [11] A. Subramanian and A. H. Sayed, "Joint rate and power control algorithms for wireless networks," *IEEE Trans. on Signal Processing*, vol. 53, no. 11, pp. 4204-4214, 2005.
- [12] T. S. Rappaport, *Wireless communications, principles and practices*, Prentice Hall, New Jersey, 1999.
- [13] W. Stallings, *Wireless Communication and Networks*, Prentice Hall, New Jersey, p. 144, 2002.
- [14] J. W. Fonda, "Energy efficient wireless sensor network protocols for monitoring and prognostics of large scale systems," Ph.D. dissertation, Missouri University of Science and Technology, Rolla, MO, 2008.
- [15] S. Jagannathan, *Discrete-time Neural Network Control of Nonlinear Systems*, Taylor & Francis, London, UK, 2006.