A Minimum Variance Rate and Power Update Algorithm for Wireless Networks

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Abstract—**A joint rate and power control algorithm is proposed for distributed wireless networks. The algorithm is robust to uncertainties in the network dynamics and is shown to achieve better SIR performance than a conventional scheme.**

I. Introduction

The evolution of mobile wireless communication and sensor networks has greatly triggered the interest in finding more efficient power control algorithms. This is due to the fact that power consumption is a key limiting factor in the performance of wireless networks. This limitation is further compounded by the fact that nodes need to cater to desired data rates, which in turn require the SNR level, and consequently the power level, to be above certain desired values. It then follows that a fundamental tradeoff exists between power levels, data rates, and congestion rates in a network. There have been many power control algorithms that have been investigated in the literature. Some of the initial distributed power control strategies have been given in [1] and [2], which balance the signal to interference ratios in a distributed way. The approaches from [3], [4] include quality of service (QoS) requirements, while the Kalman filtering approach from [5] uses admission control as the central QoS issue. Still most of these solutions do not combine in a cohesive manner the requirements of power, data rate, and congestion. For instance, the above solutions may not perform well when the desired rates in the network vary due to the use of certain rate adaptation or congestion control algorithms. Allowing for such variable data rates is desirable nowadays in view of the availability of newer wireless devices that support multiple data rates. In this paper, following the approach of [8], we propose a joint rate and power control strategy that maintains a minimum bound on the variance between the actual and desired SIR levels.

II. Network Model

We consider a sensor network operating under dynamic network conditions. Some of the nodes perform important tasks like routing and congestion control for high data rate communications. They also handle some data and network processing for other nodes that may be connected to them. We will assume a protocol similar to the one proposed in [9], where nodes are organized into local clusters or cells with one node acting as the master node. Any node that wishes to communicate is allowed to do so only with the master node and using a time slot. A time slot is allocated to any node that wishes to communicate in a cell, and the nodes communicating during the same time-slot in other cells cause interference in this cell. The Signal-to-Interference-plus-Noise-Ratio (SIR) for node i at time k on an uplink channel is

$$\gamma_i(k) = \frac{G_{ii}(k)p_i(k)}{\sum_{j\in\mathbf{A}} G_{ij}(k)p_j(k) + \sigma_i^2(k)} \tag{1}$$

where G_{ij} is the channel gain from the $j-th$ node to the intended master node of the $i-th$ cell, p_i is the transmitting power from the $i-th$ node, σ_i^2 is the power of white Gaussian noise at the receiver of the master node that node i is connected to, and $\mathbf{A}$ is the set of nodes that are interfering with node i. Figure 1 shows a schematic representation with three cells, three master nodes, and active and interfering nodes.

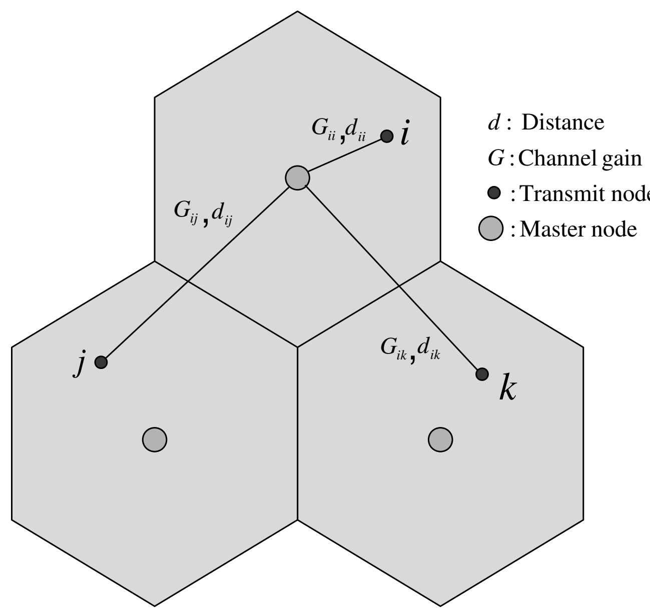

Fig. 1. *A schematic representation with three cells, three master nodes, and active and interfering nodes. The active node is node i and the interfering nodes are nodes j and k.*

III. Power and Rate Control Strategy

Let $f_i(k)$ denote the flow rate at node i at time k. We shall assume that each node in the network employs the following flow-rate control algorithm every time period:

$$\boxed{f_i(k+1) = f_i(k) + \mu[d(k) - c(k)f_i(k)]} \tag{2}$$

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where $\mu > 0$ is a step-size parameter and $c(k)$ is a measure of the amount of congestion in the network [1]. Moreover, $d(k)$ controls the rate increase per iteration. Now, in view of Shannon's capacity formula, the flow rate $f_i(k)$ demands an SIR level $\gamma_i'(k)$ that is given by

$$f_i(k) = \frac{1}{2}\log_2[1 + \gamma_i'(k)] \tag{3}$$

Using this fact and the update (2), we find that the desired SIR, in dB scale, should vary according to the rule

$$\boxed{\bar{\gamma}_i'(k+1) = [1 - \mu c(k)]\bar{\gamma}_i'(k) + \mu' d(k)} \tag{4}$$

where $\mu' = 20\mu/\log_2(10)$ and $\bar{\gamma}_i(k) = 10\log\gamma_i(k)$.

We shall initially assume that each node in the network adjusts its power according to the power control algorithm:

$$\boxed{\bar{p}_i(k+1) = \bar{p}_i(k) + \alpha_i[\bar{\gamma}_i'(k) - \bar{\gamma}_i(k)]} \tag{5}$$

where α_i is a step-size parameter that is allowed to vary from one node to another and $\gamma_i(k)$ is a measurement of the actual SIR that is achieved by $p_i(k)$. Now let

$$\beta_i(k) = \frac{G_{ii}(k)}{\sum\limits_{j\in\mathcal{A}} G_{ij}(k)p_j(k) \; + \; \sigma_i^2(k)}$$

denote the scaling factor that determines how $p_i(k)$ affects the achieved $\gamma_i(k)$ in (5), i.e.,

$$\gamma_i(k) = \beta_i(k)p_i(k)$$

or, equivalently, in dB scale,

$$\boxed{\bar{\gamma}_i(k) = \bar{\beta}_i(k) \; + \; \bar{p}_i(k)} \tag{6}$$

We refer to $\bar{\beta}_i(k)$ as the effective channel gain. We shall assume that $\bar{\beta}_i(k)$ varies according to the model

$$\bar{\beta}_i(k+1) = \bar{\beta}_i(k) \; + \; n_i(k)$$

where $n_i(k)$ is a zero-mean disturbance of variance σ_n^2 and is independent of $\bar{p}_i(k)$. Substituting this model for $\bar{\beta}_i(k)$ into (6), we find that the achieved $\bar{\gamma}_i(k)$ varies according to the rule:

$$\boxed{\bar{\gamma}_i(k+1) = (1-\alpha_i)\bar{\gamma}_i(k) + \alpha_i\bar{\gamma}_i'(k) + n_i(k)} \tag{7}$$

Our objective is to design the power control sequence $\{p_i(k)\}$ such that the actual SIR levels $\{\gamma_i(k)\}$ will tend to the desired SIR levels $\{\gamma_i'(k)\}$. We shall address this design problem by formulating a robust quadratic control problem as follows. First, we drop the node index i for simplicity of notation (it is to be understood that the resulting control mechanism is implemented at each node). Second, we introduce the two-dimensional state vector:

$$x_k \triangleq \begin{bmatrix} \bar{\gamma}(k) \\ \bar{\gamma}'(k) \end{bmatrix}$$

[1]Note that $c(k)$ could be determined based on the SIR estimation as well. When a one step ahead predicted SIR is less than the actual desired value, $c(k)$ takes higher value than otherwise.

Then combining (4) and (7) we arrive at the state-space model:

$$x_{k+1} = \begin{bmatrix} 1-\alpha & \alpha \\ 0 & 1-\mu c(k) \end{bmatrix} x_k \; + \; \begin{bmatrix} n(k) \\ \mu' d(k) \end{bmatrix}$$

or, more compactly,

$$x_{k+1} = A_k x_k + w_k \tag{8}$$

where the 2×2 coefficient matrix A_k is given by

$$\boxed{A_k = \begin{bmatrix} 1-\alpha & \alpha \\ 0 & 1-\mu c(k) \end{bmatrix}} \tag{9}$$

and where w_k is a 2×1 zero-mean random vector with covariance matrix

$$\boxed{Q = Ew_k w_k^T = \begin{bmatrix} \sigma_n^2 & \\ & \mu'^2\sigma_d^2 \end{bmatrix}} \tag{10}$$

In order to drive $\gamma_i(k)$ towards the desired level $\gamma_i'(k)$ we shall employ a control sequence u_k in (8) as follows:

$$\boxed{x_{k+1} = A_k x_k + Bu_k + w_k} \tag{11}$$

for some given 2×2 matrix B and 2×1 control sequence u_k. For example, let

$$u_k = \begin{bmatrix} u_p(k) \\ u_f(k) \end{bmatrix}$$

denote the individual entries of u_k. Then choosing

$$B = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$$

simply amounts to adding a control signal $u_p(k)$ into the power update (5). Likewise, choosing

$$B = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

amounts to adding a control signal $u_f(k)$ into the desired SIR update (4). More generally, for arbitrary choices of B, the control signals that are added into the updates for $\{\bar{p}_i(k), f_i(k)\}$ are combinations of $\{u_p(k), u_f(k)\}$.

In addition to employing a control sequence $\{u_k\}$, we shall assume that we have access to output measurements that are related to the state vector as follows:

$$\boxed{y_k = Cx_k + v_k} \tag{12}$$

for some known matrix C and where v_k denotes measurement noise with covariance matrix R,

$$\boxed{R = Ev_k v_k^T}$$

Usually, $C = I$ so that the entries of y_k correspond to noisy measurements of the actual and desired SIR levels $\{\bar{\gamma}(k), \bar{\gamma}'(k)\}$. We will now propose a design procedure that takes into account uncertainties that arise due to the lack of perfect knowledge about the network conditions. For example, the congestion control function $c(k)$ is usually not known exactly and has to be estimated, and this estimation process introduces errors in the assumed state-space model. Thus assume that the factor $c(k)$ can be modelled as

$$c(k) = \bar{c}(k) + G\delta(k)\bar{D} \tag{13}$$

with $\delta(k)$ being a zero mean random noise with variance ρ_Δ, G and $\bar{D}$ are known scalars, and $\bar{c}(k)$ is bounded as

$$c_l \leq \bar{c}(k) \leq c_u \tag{14}$$

for some known positive scalars $\{c_l, c_u\}$. In other words, we allow for both deterministic and stochastic uncertainties in $c(k)$. In this way, the matrices A_k themselves are not known exactly but they are now modelled as $A_k = \bar{A}_k + \delta A_k$ where

$$\boxed{\bar{A}_k = \begin{bmatrix} 1-\alpha & \alpha \\ 0 & 1-\mu\bar{c}(k) \end{bmatrix}} \tag{15}$$

and

$$\delta A_k = G\delta_k D \tag{16}$$

where

$$G = \bar{M}, \quad D = \begin{pmatrix} 0 & 0 \\ 0 & -\mu\bar{D} \end{pmatrix} \tag{17}$$

We shall design the control sequence $\{u_k\}$ as follows. First, we use the robust algorithm of [12] to estimate the state of perturbed state-space models as in (15)–(16). Then, the control sequence $\{u_k\}$ will be designed such that an upper bound on the following stochastic quadratic cost function $\mathcal{J}$ is minimized:

$$\mathcal{J} = E\left\{\sum_{k=0}^{\infty} \|Lx_k\|^2\right\}$$

with $L = [\ 1 \quad -1\ ]$, and where E denotes the expectation operator. This choice of L results in

$$Lx_k = \bar{\gamma}(k) - \bar{\gamma}'(k)$$

so that $\|Lx_k\|^2$ is a measure of the energy of the difference between $\{\bar{\gamma}(k), \bar{\gamma}'(k)\}$. The resulting control will guarantee the following performance over all models $\{\bar{A}_k + \delta A_k\}$. Let $\tilde{x}_k = x_k - \hat{x}_k$ denote the state estimation error. Then the construction will determine state estimates $\{\hat{x}_k\}$, and a control sequence $\{u_k\}$ as a function of these state estimates, such that an upper bound on $E\|Lx_k\|^2$ is minimized. Moreover, it will hold that the effect of the noise disturbances on the error $\{\bar{\gamma}(k) - \bar{\gamma}'(k)\}$ will be limited in the following manner:

$$E\left\{\sum_{k=0}^{\infty} |\bar{\gamma}(k) - \bar{\gamma}'(k)|^2\right\} < \nu^2\left\{\sum_{k=0}^{\infty}\left(\|w_k\|^2 + \|v_k\|^2\right)\right\} + b \tag{18}$$

for some constant $b > 0$ and for the smallest possible ν^2, and over all noise sequences $\{w_k, v_k\}$. The following statement is specialized to $B = I$.

A Minimum Variance Power and Rate Control Algorithm. Let

$$A_1 = \begin{bmatrix} 1-\alpha & \alpha \\ 0 & 1-\mu c_l \end{bmatrix}, \quad A_2 = \begin{bmatrix} 1-\alpha & \alpha \\ 0 & 1-\mu c_u \end{bmatrix}$$

Given a 1×2 vector L, the following is a robust joint power and rate-flow control strategy:

1. Introduce a 2×2 matrix A_f and a 2×1 vector B_f. Determine A_f and B_f in the following manner [12]. Given scalars $\{\gamma_1 > 1, \gamma_2 > 1\}$, solve the following convex optimization problem over the variables $\{P_1, P_2, Q_1, Q_2, W\}$:

$$\min \ \ \mathrm{Tr}(P_1 + P_2 + W)\frac{\gamma}{\gamma - 1} \tag{19}$$

subject to the conditions

$$\left(\begin{array}{cc|cc} Z' & 0 & A_m^T P_1 & \hat{J} \\ 0 & \gamma_2^{-1}P_2 & 0 & Q_1 \\ \hline P_1 A & 0 & P_1 & 0 \\ \hat{J}^T & Q_1^T & 0 & P_2 \end{array}\right) > 0 \tag{20}$$

and

$$\begin{pmatrix} W & Q_2 \\ Q_2^T & P_2 \end{pmatrix} > 0 \tag{21}$$

with $P_1 > I$ and $P_2 > I$, where

$$\begin{aligned} Z' &= \gamma_1^{-1}P_1 - \rho_\Delta G^T D^T (P_1 + P_2) DG \\ \gamma &= \min\{\gamma_1, \gamma_2\} \end{aligned}$$

and

$$\hat{J} = -C^T Q_2 - Q_1 + A^T P_2 \tag{22}$$

Determine A_f and B_f as

$$\begin{aligned} A_f &= (Q_1 P_2^{-1})^T \\ B_f &= (Q_2 P_2^{-1})^T \end{aligned}$$

2. Using the just found $\{A_f, B_f\}$, define

$$\breve{A}_1 = \begin{bmatrix} A_1 - K_c & K_c \\ A_1 - A_f - B_f C & A_f \end{bmatrix}$$

$$\breve{A}_2 = \begin{bmatrix} A_2 - K_c & K_c \\ A_2 - A_f - B_f C & A_f \end{bmatrix}$$

$$\bar{B} = \begin{bmatrix} I & 0 \\ I & -B_f \end{bmatrix}$$

for some 2×2 matrix K_c to be determined. Determine K_c, X, and the smallest positive ν^2 that guarantee

$$\begin{bmatrix} \tilde{H}_m & -\breve{A}_m^T X \bar{B} \\ -\bar{B}^T X \breve{A}_m & \nu^2 I - \bar{B}^T X \bar{B} \end{bmatrix} > 0$$

where

$$\tilde{H}_m = X - \breve{A}_m^T X \breve{A}_m - \tilde{L}^T \tilde{L}, \quad m = 1, 2$$

with

$$\tilde{L} = [\ L \quad 0\ ]$$

Then set

$$\begin{aligned} u_k &= -K_c \hat{x}_k \\ \hat{x}_{k+1} &= A_f \hat{x}_k \ + \ B_f y_k \ + \ u_k \end{aligned}$$

3. Partition u_k as

$$u_k = \begin{bmatrix} u_p(k) \\ u_f(k) \end{bmatrix}$$

and update the rate flow and the power at the relevant node as follows. Let $\kappa = (\log_2(10))/20$. Then

$$\begin{aligned}\bar{\gamma}'(k) &= f_i(k)/\kappa \\ \bar{p}_i(k+1) &= \bar{p}_i(k) + \alpha_i[\bar{\gamma}_i'(k) - \bar{\gamma}_i(k)] \;+\; u_p(k) \\ f_i(k+1) &= f_i(k) + \mu[d(k) - c(k)f_i(k)] + \kappa u_f(k)\end{aligned}$$

We may note that the above optimization problem is performed only once off-line to get the control parameters.

IV. Simulation Results

To illustrate the performance of the proposed algorithm, we simulate the model proposed in [10] for the channel gain from the $i-$th node to its master node. In this model, G_{ii} has a log-normal distribution, namely

$$G_{ii} = S_0 d_{ii}^{-\beta} 10^{\alpha/10} \tag{23}$$

where S_0 is a function of the carrier frequency, β is the path loss exponent (PLE), and d_{ii} is the distance of node i from its master node. The value of β depends on the physical environment and varies between 2 and 6 (usually 4). Moreover, α is a zero mean Gaussian random variable with variance σ_α^2, which usually ranges between 6 and 12.

Let $g_i \triangleq \ln(G_{ii})$. Then, based on the above statistical characterization, the random variable g_i has a Gaussian distribution:

$$f_{g_i}(g) = \frac{1}{\sigma_g\sqrt{2\pi}}\; e^{-\frac{(g-\bar{g})^2}{2\sigma_g^2}}$$

with mean

$$\bar{g} = \ln(S_0) - \beta\ln(d_{ii})$$

and standard deviation

$$\sigma_g = (\sigma_\alpha \ln 10)/10$$

We shall neglect the effect of fast fading since the power update algorithm generally has a large time period. On the other hand, for the shadowing effect, we shall assume that the correlation sequence for the random process $\{g_i(k) = \ln G_{ii}(k)\}$ is given by

$$R_g(\tau) \triangleq E g_i(k)g_i(k-\tau) \;=\; \sigma_g^2 a^{|\tau|}, \quad a = 10^{-vT/D}$$

where σ_g^2 ranges between 3 and 10 dB, v is speed, T is the time period for channel probing, and D is the distance at which the normalized correlation reaches the value 1/10. We assume that the velocity of the nodes is small enough so that we can approximate $a \approx 1$ and, hence, $R_g(\tau) \approx \sigma_g^2$. We simulate a network consisting of 9 cells with 8 nodes per cell. Queries through nodes arrive at the system with a poison distribution with arrival rate θ. The service (or holding) time for each user is an exponential distribution with average holding time give by $1/\phi$. We consider a traffic load between 5.5 and 11 Erlang per cell, where the ratio of arrival rate to average service time $\left(\frac{\theta}{\phi\times 9}\right)$ denotes the traffic in Erlang per cell. New nodes need to have atleast 12 dB SIR to get admission into the system. To maintain a uniform power distribution between nodes we vary the master node randomly among the nodes. The maximum acceptable power that a node can transmit is the amount of power that causes the SIR to be 20dB without any other user interference at a distance of 25 meters. The value of α_i used in the proposed algorithm for every node i is 0.2. Fig. 2 illustrates the performance of the proposed algorithm in comparison to the algorithm [7]:

$$\bar{p}_i(k+1) = \bar{p}_i(k) + \alpha[\bar{\gamma}_i(k) - \bar{\gamma}_i'(k)] \tag{24}$$

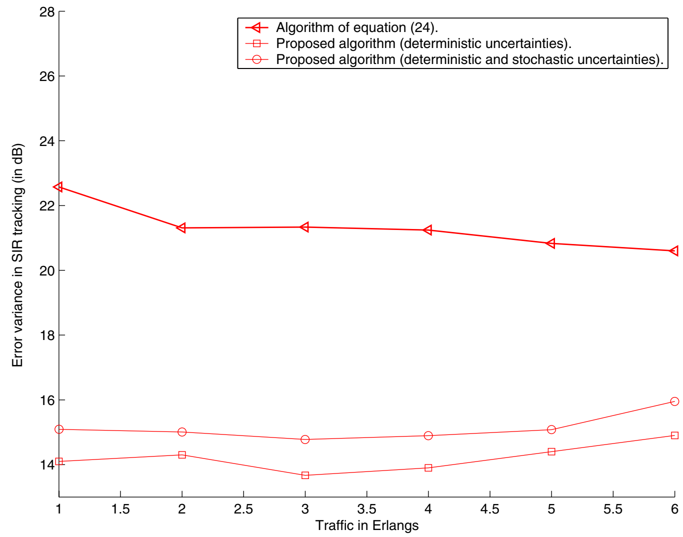

Fig. 2. Variance in SIR tracking.

Appendix A : Robust Performance

In this appendix, we show that the algorithm of Section 5 is stable and ensures a robust performance level of ν^2, as in (18). Define

$$\eta_k \triangleq \begin{pmatrix} x_k \\ \hat{x}_k \end{pmatrix}, \quad o_k \triangleq \begin{pmatrix} w_k \\ v_k \end{pmatrix} \tag{25}$$

Let $V(\eta_k) = \eta_k^T X \eta_k$, for some $X > 0$ to be determined in order to satisfy the inequality

$$EV(\eta_{k+1}) - EV(\eta_k) - \nu^2(w_k^T w_k + v_k^T v_k) + E\tilde{z}_k^T\tilde{z}_k < 0 \tag{26}$$

where $\tilde{z}_k = \tilde{L}\eta_k = \bar{\gamma}(k) - \bar{\gamma}'(k)$, with all the quantities as defined in Sec. 5. We will show that, for a given A_f and B_f, if X is determined such that the above inequality is satisfied, then (18) is guaranteed. Indeed, if we sum inequality (26) over k, and if we assume that the system is exponentially stable (which will be shown at the end of this appendix), we get for all $w_k, v_k \in l_2$,

$$E\left\{\sum_{k=0}^{\infty}|\bar{\gamma}(k) - \bar{\gamma}'(k)|^2\right\} < EV(\eta_0) + \nu^2\left\{\sum_{k=0}^{\infty}\|w_k\|^2 + \|v_k\|^2\right\} \tag{27}$$

as desired. Now assume a control structure of the form

$$\hat{x}_{k+1} = A_f\hat{x}_k + B_f y_k + u_k, \;\; u_k = -K_c\hat{x}_k \tag{28}$$

for some given $\{A_f, B_f\}$ and unknown K_c. Combining this equation with

$$\begin{aligned} x_{k+1} &= (\bar{A}_k + \delta A_k)x_k + u_k + w_k \\ y_k &= Cx_k + v_k \end{aligned}$$

and assuming, for example, that $\bar{A}_k + \delta A_k$ is equal to one of the boundary points, say $\breve{A}_1$, we find that η_k satisfies the state-space model:

$$\eta_{k+1} = \breve{A}_1 \eta_k + \bar{B} \begin{pmatrix} w_k \\ v_k \end{pmatrix} \tag{29}$$

where

$$\breve{A}_1 = \begin{pmatrix} A_1 - K_c & K_c \\ A_1 - A_f - B_f C & A_f \end{pmatrix}, \quad \bar{B} = \begin{pmatrix} I & 0 \\ I & -B_f \end{pmatrix} \tag{30}$$

Likewise, for the boundary point $\breve{A}_2$. Using (29) and expanding (26) gives

$$\begin{aligned} &\eta_k^T \breve{A}^T X \breve{A} \eta_k - \eta_k^T X \eta_k + \eta_k^T \breve{A}^T X \bar{B} o_k + o_k^T \bar{B}^T X \breve{A} \eta_k \\ &- \nu^2 o_k^T o_k + o_k^T \bar{B}^T X \bar{B} o_k + \eta_k^T \tilde{L}^T \tilde{L} \eta_k < 0 \end{aligned} \tag{31}$$

With $\breve{A}$ taking values between $\breve{A}_1$ and $\breve{A}_2$, condition (31) is equivalent to requiring

$$-\begin{pmatrix} \eta_k^T & o_k^T \end{pmatrix} \begin{bmatrix} \tilde{H}_m & -\breve{A}_m^T X \bar{B} \\ -\bar{B}^T X \breve{A}_m & \nu^2 I - \bar{B}^T X \bar{B} \end{bmatrix} \begin{pmatrix} \eta_k \\ o_k \end{pmatrix} < 0 \tag{32}$$

where

$$\tilde{H}_m = X - \breve{A}_m^T X \breve{A}_m - \tilde{L}^T \tilde{L}, \quad m = 1, 2$$

Hence, (32) is satisfied if

$$\begin{pmatrix} \tilde{H}_m & -\breve{A}_m^T X \bar{B} \\ -\bar{B}^T X \breve{A}_m & \nu^2 I - \bar{B}^T X \bar{B} \end{pmatrix} > 0, \quad m = 1, 2 \tag{33}$$

for some K_c, ν^2, and $X > 0$, as desired. Inequality (33) also implies that the system is stable because of the following reasons. Note that, for any boundary point $\breve{A}_m$, the Lyapunov function $V(.)$ satisfies, in the absence of noise,

$$V(\eta_k) - V(\eta_{k+1}) = \eta_k^T (X - \breve{A}_m^T X \breve{A}_m) \eta_k \tag{34}$$

But inequality (33) implies that $\tilde{H}_m > 0$ for all $\breve{A}$ taking values between $\breve{A}_1$ and $\breve{A}_2$. This in turn implies that $V(\eta_{k+1}) - V(\eta_k) < 0$ for all uncertainties. Hence, the process η_k is exponentially stable.

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