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Uncertain Networked Control Systems with Non-Stationary Packet Dropouts

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Abstract— This paper examines the prominent features of networked control systems (NCS). A robust H_{oo} controller designed for a class of uncertain networked control systems with random packet losses. The uncertainties are norm bounded and packet dropout assumed to obey Bernoulli random binary distribution. The method based on evolutionary programming (EP) search technique. An observer-based feedback controller constructed to robustly stabilize the system in the mean-square sense. The simulation examples indicate the good performance of the developed controller.

Keywords— Networked control systems; Evolutionary programming technique; Network delays; Packet losses.

I. Introduction

Networked control systems (NCS) are comprised of the system to be controlled and of actuators, sensors, and controllers whose operation is coordinated through some form of communication network. The widely accepted feature of NCS is that the component elements are spatially distributed, may operate in an asynchronous manner, but have their operation coordinated to achieve some overall objective, see Fig. 1. The proliferation of these systems has raised fundamentally new questions in communications, information processing, and control dealing with the relationship between operations of the network and the quality of the overall systems operation. It turns out that networked control systems (NCS) have shown to provide low cost, high reliability, less wiring and easy maintenance [1] over traditional point-to-point architecture communication. On the other hand, NCS have also posed some challenges due to its inherent shortcomings such as packet loss, delays and bandwidth constraints, which can degrade performance or be a source of instability. Packet losses can occur in NCS when there are node failure or message collisions [2] from sensor either to controller or from controller to actuator or both. Different approaches have used to model packet dropout between sensor and controller, including switch system approach [3], and Markovian jump parameter [4]. In this work, we consider that packet losses occur simultaneously from sensor to controller and from controller to actuator. Considerable research efforts addressed modeling, stability analysis and control design problems of NCS [1]-[5]. Robust H_{oo} control, being one of such extensive effort, were considered in various class of NCS with uncertainties and packet losses between sensor and controller [6], [7], [8], by establishing necessary and sufficient conditions expressed in terms of Linear Matrix Inequalities (LMI). It turns out from the published results that NCS belongs to a wide class of switched time-delay systems [11] from which it becomes clear there are several standing issues. Chief among these are the degree of conservatism, solution feasibility and reproducibility of results, to name a few.

NCS lie at the intersection of control and communication theories. Traditionally, control theory focuses on the study of interconnected dynamical systems linked through *"ideal channels*", whereas communication theory studies the transmission of information over "*imperfect channels*". This paper is written from a controls perspective and attempts to systematically address several key issues that make NCS distinct from other control systems:

Band-Limited Channels: Any communication network can only carry a finite amount of information per unit of time. This limitation poses significant constraints on the operation of NCS. Inspired by Shannon's results on the maximum bit rate that a communication channel can carry reliably, a significant research effort has been devoted to the problem of determining the minimum bit rate that is needed to stabilize a linear system through feedback over a finite capacity channel [12]–[19].

Sampling and Delay: To transmit a continuous-time signal over a network, the signal must be sampled, encoded in a digital format, transmitted over the network, and finally the data must be decoded at the receiver side. This process is

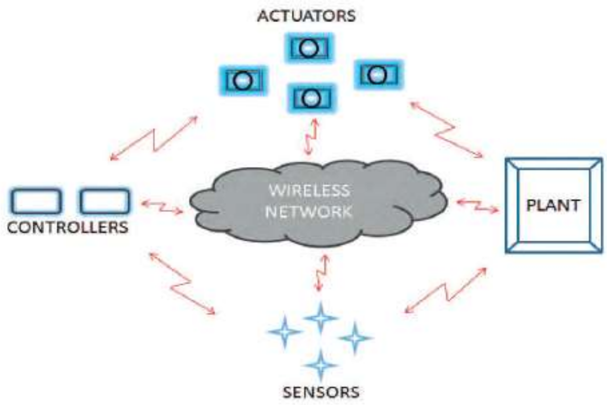

Fig. 1. NCS architecture

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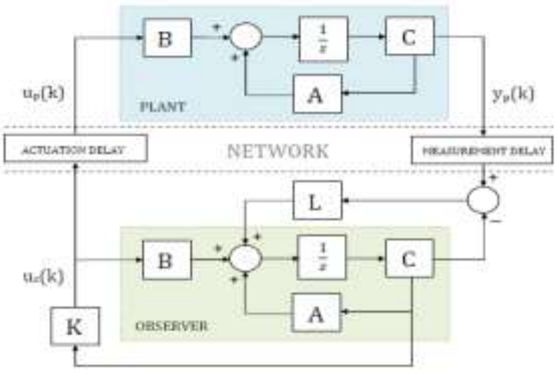

Fig. 2. Block diagram of the control system

significantly different from the usual periodic sampling in digital control. The overall delay between sampling and eventual decoding at the receiver can be highly variable because both the network access delays (i.e., the time it takes for a shared network to accept data) and the transmission delays (i.e., the time during which data are in transit inside the network) depend on highly variable network conditions such as congestion and channel quality.

Packet Dropout: In NCS, there is a possibility that data may be lost while in transit through the network. Packet dropouts result from transmission errors in physical network links (which is far more common in wireless than in wired networks) or from buffer overflows due to congestion. Long transmission delays sometimes result in packet reordering, which essentially amounts to a packet dropout if the receiver discards outdated arrivals.

Systems Architecture: Fig. 1 shows the general architecture of an NCS. In this figure, encoder blocks map measurements into streams of B–symbols that can be transmitted across the network. Encoders serve two purposes: they decide when to sample a continuous-time signal for transmission and what to send through the network. Conversely, decoder blocks perform the task of mapping the streams of symbols received from the network into continuous actuation signals. One could also include in Fig. 1 encoding/decoding blocks to mediate the controller's access to the network.

The main contributions of the paper are
• Demonstrating the prominent features of delays and packet dropouts in NCS by means of simulation of observer-based control system,
• Applying an evolutionary programming (EP) technique to determine the controller gains,
• Disclosing the flexibility and effectiveness of the system design framework.

II. Nonstationary Packet Dropouts

To demonstrate the working of networked control system, we look Fig. 2, where the plant and an observer-based controller is connected by means of a lossy network. The L matrix is the observer gain matrix and the K matrix is the state-feedback gain matrix. The measurement delays are generated using random number generators as shown in Fig. 3, which is divided into two sub-blocks. The lower sub-block decides if at a given instant a measurement delay occurs or not. The random number generated from the *Uniform Random Number Generator 1* is compared with the variable probability p_k and if the random number 1 is less than p_k, the output of the *comparator* is 1. If the output of the comparator is 1 at a given instant, a delay occurs in the *measurement channel*. Similarly, a value of 0 at the output of the comparator implies no occurrence of delay. The *Uniform Random Number 2* defined in the range $[t_m^- \rightarrow t_m^+]$, i.e. it decides the size of the measurement delay at any given instant, if at all it were to occur. The random number 2 is multiplied with 1/0 value coming from the lower half block and supplied to the *'variable fractional delay'* block in Matlab Simulink system (Matlab 7.0) to generate a corresponding delay. Note that the variable probabilities p_k and s_k are assumed to follow certain distributions. In our study, we assume that the two probabilities undergo similar variation with time. For this example, we consider uniform triangle distribution as shown in Fig. 4. The corresponding delays occurring in measurement and actuation channels are shown in Fig. 5. Comparing Fig. 4 and Fig. 5, we see that delays that are more frequent occur when the probabilities p_k and s_k are high.

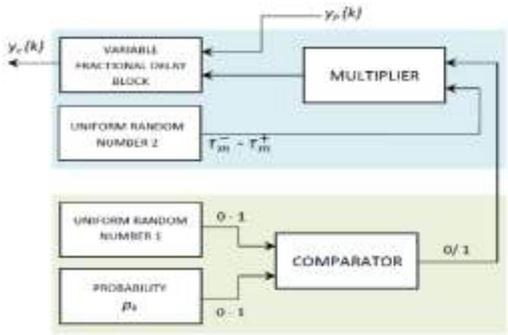

Fig. 3. Measurement delay generation block

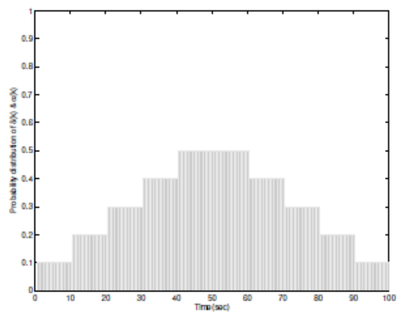

Fig. 4. Uniform triangle distribution of probabilities

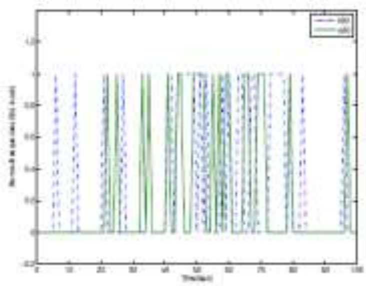

Fig. 5. Delays occurring in the communication channels

III. Four-Tank Process

A quadruple-tank process consisting of four interconnected water tanks and two pumps is considered for simulation. Its manipulated variables are voltages to the pumps and the controlled variables are the water levels in the two lower tanks. The quadruple-tank process is being built by considering the concept of two double-tank processes. The quadruple tank system presents a multi-input-multi-output (MIMO) system. Fig. 6 can visualize a schematic description of the four-tank system. The system has two control inputs (pump throughput) which can be manipulated to control the water level in the tanks. The two pumps used to transfer water from a sump into four overhead tanks.

Invoking the 'variable fractional delay' block in Matlab Simulink system to handle discrete time-varying delays and under appropriate initial conditions, the response of systems states with nonstationary dropouts is shown in Fig. 7. It is seen that our method provides faster response, smaller overshoot, and higher control precision with smaller system oscillations.

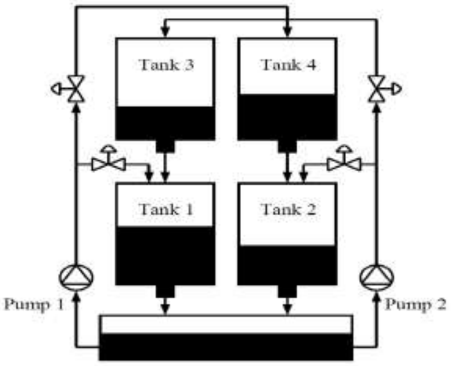

Fig. 6. Schematic diagram of quadruple tank system

IV. NCS with Uncertainties

The following assumptions are made:

- Single packet transmission
- Different data packets have same length
- Online measurement of sample data model can be obtained

Consider a class of uncertain linear system described by

$$\begin{aligned} x(k+1) &= (A+\Delta A)x(k) + Bu(k) + B_w w(k) \\ z(k) &= (G+\Delta G)x(k) + D_w w(k) \end{aligned} \quad (1)$$

where $x(k) \in \Re^n$, $u(k) \in \Re^m$ are plant states and control inputs, respectively and $z(k) \in \Re^q$, $w(k) \in \Re^q$ are the performance output and the disturbance input. Matrices A, B, G, D_w and B_w are known matrices of appropriate dimensions. Matrices ΔA and ΔC are the parametric uncertainties in the system assumed to be of the form:

$$\begin{bmatrix} \Delta A & \Delta G \end{bmatrix} = \begin{bmatrix} H_1 \\ H_2 \end{bmatrix} F(k)E \quad (2)$$

where H_1, H_2 are known real constant matrices of appropriate dimensions and F (k) satisfy F (k) FT (k) ≤ I.

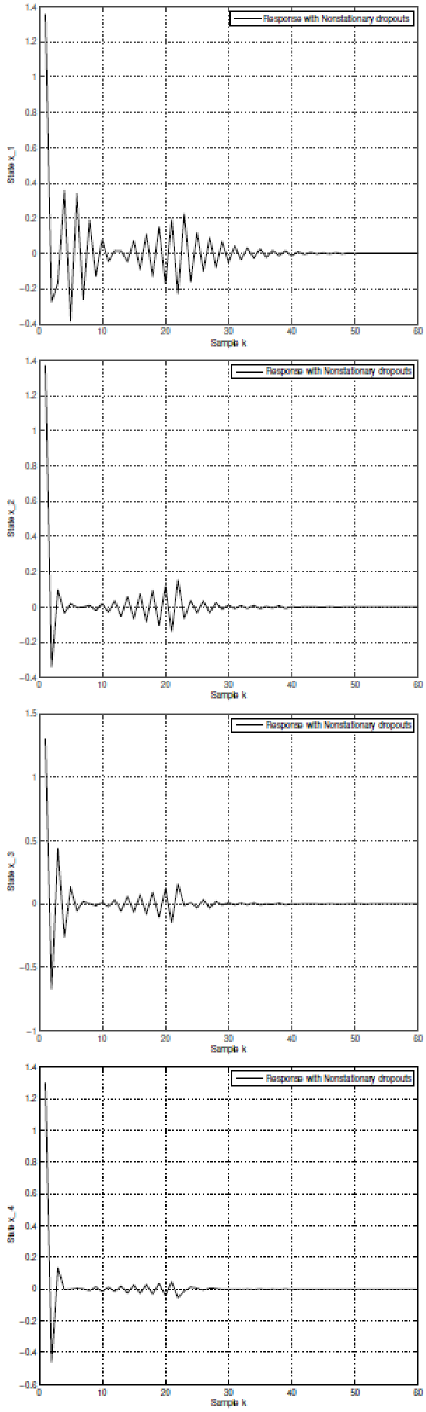

Fig. 7. State trajectories for nonstationary dropouts

The measurement with random communication packet loss is described by

$$y(k) = \alpha(k)Cx(k) + Dw(k) \quad (3)$$

where $y(k) \in \Re^p$ is the measured output vector, C and D are known real matrices and the random $\alpha(k) \in \Re$, which described the packet losses between the sensor and controller is a Bernoulli distributed white sequence with the following properties

$$\begin{aligned} prob[\alpha(k)=1] &= \mathbb{E}[\alpha(k)] = \bar{\alpha} \\ prob[\alpha(k)=0] &= \mathbb{E}[1-\alpha(k)] = 1-\bar{\alpha} \end{aligned} \quad (4)$$

The dynamics of the observer-based control scheme for the system (1) is described by

$$\begin{aligned} \hat{x}(k+1) &= A\hat{x}(k) + Bu(k) + L(y(k) - \bar{\alpha}C\hat{x}(k)) \quad (5) \\ \hat{u}(k) &= -K\hat{x}(k) \\ u(k) &= \beta(k)\hat{u}(k) \end{aligned}$$

where $\hat{x}(k) \in \Re^n$ is the estimate of the system (1), $\hat{u}(k) \in \Re^m$ is the control input without transmission missing, and $L \in \Re^{n\times m}$ and $K \in \Re^{m\times n}$ are the observer and controller gains respectively. The random variable $\beta(k) \in \Re$ described the packet losses from the controller to actuator, and is mutually independent of $\alpha(k)$ and also a Bernoulli distributed white sequence with

$$\begin{aligned} prob[\beta(k) = 1] &= \mathbb{E}[\beta(k)] = \bar{\beta} \\ prob[\beta(k) = 0] &= \mathbb{E}[1 - \beta(k)] = 1 - \bar{\beta} \end{aligned} \quad (6)$$

Therefore the estimation error will be :

$$e(k) = x(k) - \hat{x}(k) \quad (7)$$

On substituting (3) and (5) into (1) and (7), the closed-loop system is obtained as

$$\begin{aligned} x(k+1) &= (A + \Delta A)x(k) - \beta(k)BKx(k) \\ &+ \beta(k)BKe(k) + B_w w(k) \\ e(k+1) &= \Delta Ax(k) + (A - \bar{\alpha}LC)e(k) \\ &- (\alpha(k) - \bar{\alpha})LCx(k) \\ &+ (B_w - LD)w(k) \end{aligned} \quad (8)$$

Rearranging

$$\begin{aligned} x(k+1) &= (A + \Delta A - \bar{\beta}BK)x(k) \\ &- (\beta(k) - \bar{\beta})BKx(k) \\ &+ (\beta(k) - \bar{\beta})BKe(k) \\ &+ \bar{\beta}BKe(k) + B_w w(k) \\ e(k+1) &= \Delta Ax(k) + (A - \bar{\alpha}LC)e(k) \\ &- (\alpha(k) - \bar{\alpha})LCx(k) \\ &+ (B_w - LD)w(k) \end{aligned} \quad (9)$$

This can be written in compact form below:

$$\eta(k+1) = \bar{A}\eta(k) + \kappa\tilde{A}\eta(k) + \bar{B}_w w(k) \quad (10)$$

where

$$\begin{aligned} \eta(k) &= \begin{bmatrix} x(k) \\ e(k) \end{bmatrix}, \\ \bar{A} &= \begin{bmatrix} A + \Delta A - \beta BK & \bar{\beta}BK \\ \Delta A & A - \bar{\alpha}LC \end{bmatrix}, \\ \kappa &= \begin{bmatrix} (\beta(k) - \bar{\beta})I & 0 \\ 0 & (\alpha(k) - \bar{\alpha})I \end{bmatrix}, \\ \tilde{A} &= \begin{bmatrix} -BK & BK \\ LC & 0 \end{bmatrix}, \bar{B} = \begin{bmatrix} B_w \\ B_w - LD \end{bmatrix} \end{aligned}$$

V. Robust H_{∞} Controller Design

The main objective of this work is to develop an improved approach for the design of controller (5) in the presence of parametric uncertainty and random packet losses, simultaneously from the sensor to controller and from controller to actuator, such that the close loop system (9) satisfies the following two requirements:

1) *The closed loop system (10) is exponentially mean-square stable with w(k) =0*
2) *Under the zero initial condition, the controller output $z(k)$ achieved $\mathcal{H}_\infty$ disturbance-rejection performance.*

Mathematically, the condition above can be stated as follows: *The closed-loop system (10) is said to be exponentially mean-square stable with $w(k) = 0$ if there exist constant $\phi > 0$ and $\tau \in (0, 1)$ such that*

$$\mathbb{E}\left\{\|\eta(k)\|^2\right\} \le \phi\tau^k \mathbb{E}\left\{\|\eta(0)\|^2\right\}, \forall\eta(0) \in \Re^n \quad (11)$$

The second condition can be stated as, $\forall w(k) \neq 0$, and if there exist $\gamma > 0$ then $z(k)$ satisfies:

$$\sum_{k=0}^{\infty} \mathbb{E}\left\{\|z(k)\|^2\right\} < \gamma^2 \sum_{k=0}^{\infty} \mathbb{E}\left\{\|w(k)\|^2\right\} \quad (12)$$

In what follows, we provide an evolutionary programming search technique to attain the cited objectives

VI. Evolutionary Programming Algorithm

Evolutionary programming (EP) falls into the broader category of evolutionary algorithms. Heuristic search and optimization technique was devised on the principle of natural evolution and population genetics. EP starts with a random population of points that represent different potential solutions, each representing a sample point in the search space. For each generation, all the population points (solutions) evaluated against a predefined objective function. The fittest points have more chances of evolving to the next generation. The process continues until the objective is satisfied or other stopping criteria achieved. Desirable features of EP algorithm includes, complicated mathematical model is not required and the problem constraints can be easily incorporated [9]. Secondly, convergence theory for EP is well established and it has been proved to be asymptotically converge to the global optimum with probability one, under elitist selection [10]. The following highlight the EP algorithm implementation as applied to the problem.

A. EP Algorithm

- **Step 1**: Generate randomly an n trial solutions $\{x_i, i = 1, 2, ..., n\}$ to make the parent population.The i^{th} trial solution can be written as $x_i = [p_1, ...p_m]$ where m is the dimension of the problem. Each solution in the initial population is evaluated using the objective function, J. set the solution associated with the minimum value of the objective function to J_{min} and best solution, x_{best} with objective function of J_{best}.
- **Step 2**: Each optimized parameter P_j in parent solution x_i is perturb to produce an offspring x_{n+i} by

$$x_{n+i} = x_i + \left[N(0, \sigma_1^2), ...N(0, \sigma_m^2)\right], i = 1, 2, ..., n \quad (13)$$

where $N(0, \sigma_j^2)$ is a Gaussian random variable with standard deviation σ described by

$$\sigma_j = \beta \times \frac{J(x_i)}{J_{max}} \times (p_j^{max} - p_j^{min}) \quad (14)$$

where β is a scaling factor ($\beta = 0.5$ in this problem) and $J(x_i)$ is the objective function of the of the trial solution x_i

- **Step 3**: The objective functions of the off-springs are evaluated. the minimum,J_{min} and maximum J_{max} are calculated.

- **Step 4**: If $J_{min} > J_{best}$ update the best solution x_{best}, and set $J_{best} = J_{min}$
- **Step 5**: Select randomly a set q, $q \leq 2n-1$ from the total population and compare each member of the population with members of set q (q = 5 in the present problem). A weighted value W_i of each individual x_i is calculated according to the following equation.

$$W_i = \sum_{t=1}^{q} W_t \quad (15)$$

$$W_t = \begin{cases} 1 \ if \ U > \frac{J(x_i)}{J(x_i + J(x_r))} \\ 0 \ otherwise \end{cases} \quad (16)$$

where U is a uniform random number [0,1] and x_r is a randomly selected individual from the q set.

- **Step 6**: The computed weight of all 2n individual in step 5 are ranked in descending order and the first n individual are selected to represent the parents in the next generation.
- **Step 7**: The conditions under which the search process will terminate are set. In this problem, termination conditions are (a) the number of generations since the last change of the best solution is greater than a predefined number (50); (b) the number of generations reach the maximum allowable number (500). If any of the conditions is satisfied then stop, otherwise go to back to **Step 2**.

VII. Simulation Examples

Example 1: Consider the following uncertain discrete-time system described in [1]:

$$A = \begin{bmatrix} 0.9226 & -0.6330 & 0 \\ 1.0 & 0 & 0 \\ 0 & 1.0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0.5 \\ 0 \\ 0.2 \end{bmatrix},$$

$$G = \begin{bmatrix} 0.1 & 0 & 0 \end{bmatrix}, C = \begin{bmatrix} 23.738 & 20.2287 & 0 \end{bmatrix},$$

$$D_w = 0.1, \ D = 0.2, \ E = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$$

$$H_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, B_w = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, H_2 = 0.2$$

For the purpose of simulation, we take $w(k) = \frac{1}{k^2}$, $\bar{\alpha} = \bar{\beta} = 0.95$ and $\alpha(k)$, $\beta(k)$ to be random number obeying Bernoulli distribution (that is (0,1)) a robust $\mathcal{H}_\infty$ observer-based controller was obtained with $\gamma_{min} = 0.5$ and

$$K = \begin{bmatrix} 1.2397 & 0.1108 & 0.4405 \end{bmatrix}$$
$$L = \begin{bmatrix} 0.0260 & 0.0151 & 0.0403 \end{bmatrix}^t$$

The simulation result of the state response is shown in Fig. 8, with initial condition x (0) = [1 1 1]. Although the ensuing results are comparable with those reported in [1], however our technique requires less computational load.

Example 2: Consider the discrete time system controlled over the network:

$$\begin{aligned} x(k+1) &= \begin{bmatrix} -0.2 & 0 & 0.9 \\ 0.6 & -0.9 & 0.5 \\ 0.2 & -1 & 0 \end{bmatrix} x(k) \\ &+ HF(k)E_1x(k) + HF(k)E_2u(k) \\ &+ \begin{bmatrix} 0.2 \\ 0.9 \\ 0.3 \end{bmatrix} u(k) + \begin{bmatrix} 0.1 \\ 0.1 \\ -0.2 \end{bmatrix} w(t) \\ z(k) &= \begin{bmatrix} 0.2 & 0.3 & 0.3 \end{bmatrix} x(k) + 0.7u(k) \\ C &= \begin{bmatrix} 5.7 & 6.2 & 0.5 \end{bmatrix}, \ D = 0.2 \end{aligned}$$

$$H = \begin{bmatrix} 0.1 \\ 0.1 \\ 0.2 \end{bmatrix} E_2 = 0.5, E_1 = \begin{bmatrix} 0.6 & 0.2 & 0.7 \end{bmatrix}$$

Where F (k) F^T (k) ≤ 1. Applying the LMI technique, it yields infeasible solution. Next, we proceed to implement the developed control design procedure. The disturbance w (k) was assumed to be uniformly distributed within [−0.1, 0.1] for interval k ∈ [0 → 100] and zero elsewhere. Suppose the system experiences packet losses with $\bar{\alpha} = \bar{\beta} = 0.95$; using the proposed evolutionary programming technique, we obtained γ_{min} = 2.2 and K = [0.9756 −1.3041 1.5239], L^t = [−0.0956 −0.0854 −0.0855]. The simulated state response is shown in Fig. 8, with initial condition x (0)=[0.5 -0.1 0.2].

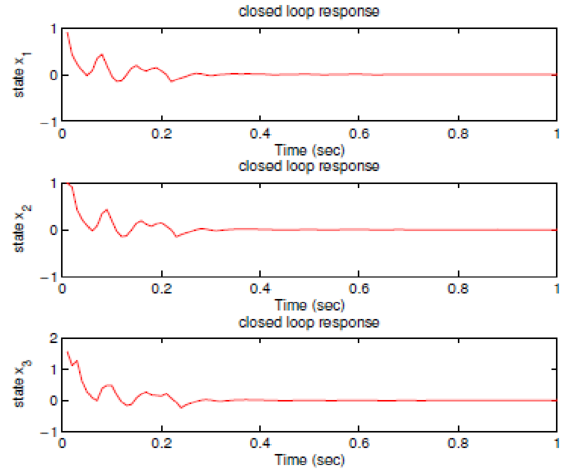

Fig. 8. Closed-loop state response under Hoo control for example 1

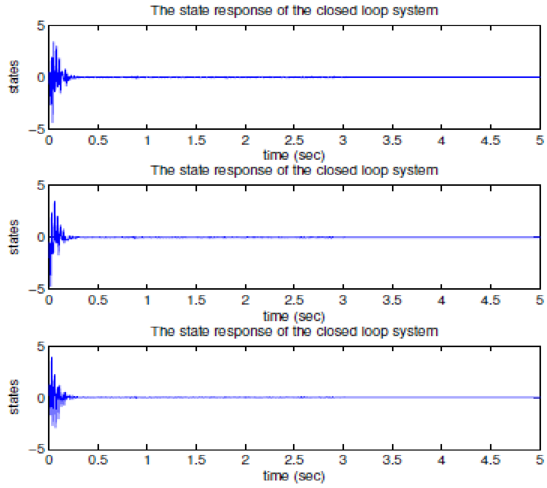

Fig. 9. Closed-loop state response under Hoo control for example 2

VIII. Conclusions

An observer-based controller was developed via evolutionary programming approach for a class of uncertain networked control system with packet losses simultaneously from the sensor to the controller and from the controller to the actuator. Using the mean square and the H_{oo} performance condition, it is established that the developed approach has the feature of systematic implementation. The simulation results have shown that the controller obtained is of good performance.

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