ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 20, April 2016

Stabilization of genetic regulatory networks on sampled-data control with leakage delays and impulses

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Abstract—This paper is concerned with stabilization of genetic regulatory networks with leakage delays and impulses. By constructing a new Lyapunov functional, stability criteria are obtained based on Lynapunov-method. Moreover the sampled-data controller is designed by solving linear matrix inequalities (LMIs). Finally, a numerical example is given to illustrate the effectiveness of the developed method.

Keywords-Genetic regulatory networks, Sampled-data control, Leakage delay, Impulses.

I. INTRODUCTION

Genetic regulatory networks(GRNs), consisting of DNA, RNA, Proteins, Small molecules and their mutual regulatory interactions, have become an important new area of research in the biological and biomedical sciences and received wide attention recently. In practical applications, leakage delay (or forgetting delay), which has been found in the negative feedback term of neural network system, is also a type of delay. Gopalsamy [3] firstly investigated the stability of the BAM neural networks with constant leakage delays. Further, Liu [8] discussed the global exponential stability for BAM neural networks with time-varying leakage delays, which extends and improves the main results of Gopalsamy. The robust stability of Markovian jump stochastic neural networks with leakage delays was investigated in [13]. In [9], the authors considered sampled data state estimator for Markovian jumping neural networks with leakage time-varying delays. In [10], the authors discussed the global asymptotic stability for genetic regulatory networks with leakage delay. They pointed out that biological networks can show changes in the dynamic behaviors or instability due to the increase of leakage delay. This means that the effect of leakage delay cannot be ignored because it can bring tendency to destabilize systems.

Compared with continuous control, the sampled-data control is more efficient, secure and useful [1]. In [2], the author considered the synchronization problem of coupled chaotic neural networks with time delay in the leakage term using sampled-data control. Lee [6] also investigated the synchronization problem of a complex dynamical network with coupling time-varying delays via sampled-data control. In [11], the authors introduced a discontinuous Lyapunov functional to consider the stability for linear systems by using the sampled-data control. Motivated by the works mentioned above, in this paper, we will investigate the stabilization of genetic regulatory networks with leakage delays based on sampled-data control. To the author's knowledge, the present study is the first attempt to discuss the stabilization for GRNs with leakage delay via sampled-data control. We firstly analyze the influence of leakage delay on stability. Once the leakage delay causes the instability of system, we will take the sampled-data control to stabilize the system. By using input delay approach, which was mentioned

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in [2,6], we investigate the stability of GRNs under the controls.

The paper is organized as follows. In section 2, we present the problem is formulation, preliminaries, assumptions, definition. In Section 3, an appropriate sampled-data controller is designed to ensure the stability of genetic regulatory networks with leakage delay and impulses. In Section 4, an illustrative example is given to show the effectiveness of our stability results. Some conclusions are proposed in Section 5.

II. MODEL DESCRIPTION AND PRELIMINARIES

The genetic regulatory network is composed of a number of genes and proteins which regulate the expression of other genes. The dynamic behavior of a genetic network can be modeled by the following differential equations:

$$\begin{cases} \dot{m}_i(t) = -a_i m_i(t) + \sum_{j=1}^{n} \omega_{ij} f_j(p_j(t-\tau_1(t)) + I_{i,} \\ \dot{p}_i(t) = -c_i p_i(t) + d_i(m_i(t-\tau_2(t)), \end{cases} \quad (1)$$

Where $a_i$and $c_i$are the degradation rates of the mRNA and protein, respectively. The $m_i(t)$ and $p_i(t)$ denote the concentrations of the mRNA and protein of the ith node at time t, respectively.d_i is the translation rate, $\tau_1(t)$ is the feedback regulation delay and $\tau_2(t)$ is the translation delay. $f(.) \in R^n$ represents the feedback regulation of the protein on the transcription, which is a monotonic function in Hill form, that is $f_j(p) = p^{h_j}/(1+p)^{h_j}$ where h_j is the Hill-coefficient. ω_{ij} is defined as follows $\omega_{ij} =$

$$\begin{cases} \alpha_{ij}, & if\ transcription\ factor\ j\ is\ an\ activator\ of\ gene\ i \\ 0, & if\ thers\ is\ no\ link\ from\ node\ j\ to\ i \\ -\alpha_{ij}, & if\ transcription\ factor\ j\ is\ a\ repressor\ of\ gene\ i. \end{cases}$$

Let $(m^*, p^*)^T$ be an equilibrium point of (1), then we will shift an intended equilibrium point $(m^*, p^*)^T$ to the origin. The transformation $x_i(t) = m_i(t) - m_i^*$, $y_i(t) = p_i(t) - p_i^*$ change system (1) into the following compact matrix form:

$$\begin{cases} \dot{x}_i(t) = -Ax(t) + Wg(y(t-\tau_1(t)), \\ \dot{y}_i(t) = -Cy(t) + Dx(t-\tau_2(t)), \end{cases}$$

A= diag $\{a_1, a_2, \dots, a_n\}$, C=diag$\{c_1, c_2, \dots, c_n\}$, $D = diag\{d_1, d_2, \dots, d_n\}$, W=$(\omega_{ij})_{n\times n}$,g(y(t))=f(y(t)+P^*) $- f(P^*)$,with g(0)=0.

In this paper, we will investigate the stabilization of genetic regulatory networks with leakage delays and impulses. The genetic regulatory networks with leakage delays and impulses can be modeled as follows:

$$\begin{cases} \dot{x}(t) = -Ax(t-\rho_1) + Wg(y(t-\tau_1(t)), \\ x_m(t_k) = \mathfrak{D}x_m(t_k^-), k \in Z^+, t = t_k, \\ \dot{y}(t) = -Cy(t-\rho_2) + Dx(t-\tau_2(t)), \\ x_p(t_k) = \mathfrak{E}x_p(t_k^-), k \in Z^+, t = t_k. \end{cases}$$

(2)

Now we investigate the stabilization of (2) via sampled-data control. The controlled system can be represented as follows:

$$\begin{cases} \dot{x}(t) = -Ax(t-\rho_1) + Wg(y(t-\tau_1(t)) + \mu(t), \\ x_m(t_k) = \mathfrak{D}x_m(t_k^-), k \in Z^+, t = t_k, \\ \dot{y}(t) = -Cy(t-\rho_2) + Dx(t-\tau_2(t)) + v(t), \\ x_p(t_k) = \mathfrak{E}x_p(t_k^-), k \in Z^+, t = t_k. \end{cases}$$

(3)

Considering the following sampled-data feedback controller:
$\mu(t) = Kx(t_k), v(t) = My(t_k)$ *where* K, M$\in R^{n\times n}$ are the sampled-data feedback controller gain matrix, t_k denotes the sample time point, $t_k \le t < t_{k+1}, k \in N$, N denotes the set of all natural number.

Assume that there exists a positive constant τ_3 such that sample interval $t_{k+1} - t_k \le \tau_3$, k ∈ N. Let $\tau_3(t) = t - t_k$, for $t \in [t_k, t_{k+1})$, then $t_k = t - \tau_3(t)$ with $0 \le \tau_3(t) \le \tau_3$.
Under the control law, the GRNs (3) can be rewritten as follows:

$$\begin{cases} \dot{x}(t) = -Ax(t-\rho_1) + Wg(y(t-\tau_1(t)) + Kx(t-\tau_3(t)), \\ x_m(t_k) = \mathfrak{D}x_m(t_k^-), k \in Z^+, t = t_k, \\ \dot{y}(t) = -Cy(t-\rho_2) + Dx(t-\tau_2(t)) + My(t-\tau_3(t)), \\ x_p(t_k) = \mathfrak{E}x_p(t_k^-), k \in Z^+, t = t_k, \end{cases} \quad (4)$$

For the above model (4), the initial values are given as
$x_i(s) = \varphi_i(s), s\epsilon(-\tau, 0), y_i(s) = \psi_i(s), s \in (-\sigma, 0)$,
Where $\tau = \max\{\rho_1, \tau_2, \tau_3\}$and $\sigma = \max\{\rho_2, \tau_1, \tau_3\}$.

In order to derive stability condition for GRNs model (4) and calculate the sampled-data feedback

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International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
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controller gain matrices K, M we need the following assumptions and lemma.

(H_1) The leakage delays ρ_1, ρ_2 are positive constants.

(H_2) The time-varying delays $\tau_1(t), \tau_2(t)$ are continuous functions satisfying $0 \le \tau_1(t) \le \tau_1$, $0 \le \tau_2(t) \le \tau_2$, $\dot{\tau}_1(t) \le \tau < 1$, where τ_1, τ_2 and τ are constants.

(H_3) There exist constants k_i^-, k_i^+ such that the genetic regulatory function $g_i(.)$ satisfies

$$k_i^- \le \frac{g_i(x) - g_i(y)}{x - y} \le k_i^+,$$

For all x, y$\in \mathbb{R}$, x$\neq y$ and i=1,2,…,n.

Remark 2.1 In assumption(H_3), k_i^-, k_i^+ are some real constants and they may be positive, zero or negative. Compared with the existing results in [12], assumption (H_3) is less conservation and less restrictive. It is obvious, when g_i is Hill function, (H_3) holds with$k_i^- = 0$. So, $g_i$can be more general than Hill function.

Lemma 2.2 (GU[4]) For any positive-definite matrix M>0, a scalar $\tau > 0$ and a function $\phi: [0, \tau] \to R^n$ such that the integrations concerned are well defined, the following inequality holds:

$$[\int_0^\tau \phi(t)dt]^T M [\int_0^\tau \phi(t)dt] \le \tau \int_0^\tau \phi^T(t) M \phi(t)dt$$

III. MAIN RESULTS

In this section, the stability analysis of system (4) is investigated based on the Lyapunov functional approach. Some sufficient conditions are obtained to ensure stability of genetic regulatory networks by designing a suitable sampled-data controller.

Theorem 3.1 Let the assumptions $H_1, H_2$and H_3hold, then the
trivial solution of system (4) is asymptotically stable, if there exist positive-definite symmetric matrices P,Q,$P_i(i = 1,2,\dots,7)$, $Q_i(i = 1,2,\dots,5)$ and positive-definite diagonal matrix Λ_1, Λ_2, such that the following LMIs hold:

$$\phi = (\varphi_{ij})_{16\times16} < 0 \qquad \text{(a)}$$

Where

$$\varphi_{1,1} = \rho_1 P_1 + P_5 + P_6 - Q_2 - Q_3\ , \varphi_{1,2} = P - S_1,$$

$$\varphi_{1,3} = -S_1 A, \varphi_{1,5} = Q_2\ , \varphi_{1,7} = Q_3 + X, \varphi_{1,16} = S_1 W$$

$$\varphi_{2,2} = \tau_2^2 Q_2 + \tau_3^2 - S_1 - S_1^T, \varphi_{2,3} = -S_1 A, \varphi_{2,7} = X$$

$$\varphi_{2,16} = S_1 W, \varphi_{3,3} = -\rho_1 P_1, \varphi_{4,4} = -P_5 - Q_2$$

$$\varphi_{5,5} = -Q_2 - Q_2^T, \varphi_{5,8} = D^T S_2^T, \varphi_{5,9} = D^T S_2^T,$$

$$\varphi_{6,6} = -P_6 - Q_3, \varphi_{6,7} = Q_3, \varphi_{7,7} = -Q_3 - Q_3^T,$$

$$\varphi_{8,8} = \rho_2 P_2 + P_3 + P_4 - Q_1 + (\tau - 1)Q_5 - \Lambda_1 L + P_7 - Q_4,$$

$$\varphi_{8,9} = Q - S_2 - Q_4, \varphi_{8,10} = -S_2 C, \varphi_{8,14} = Y + Q_4\ ,$$

$$\varphi_{8,15} = \Lambda_1 R, \varphi_{9,9} = \tau_1^2 (Q_1 + Q_5) - S_2 - S_2^T + \tau_3^2 Q_4,$$

$$\varphi_{9,9} = \tau_1^2 (Q_1 + Q_5) - S_2 - S_2^T + \tau_3^2 Q_4, \varphi_{9,10} = -S_2 C,$$

$$\varphi_{9,14} = Y, \varphi_{10,10} = -\rho_2 P_2, \varphi_{11,11} = -P_4 - Q_1\ , \varphi_{11,12} = Q_1,$$

$$\varphi_{12,12} = (\tau - 1)P_3 + (\tau - 1)Q_5 - Q_1 - Q_1^T - \Lambda_2 L,$$

$$\varphi_{12,16} = \Lambda_2 R, \varphi_{13,13} = -P_7 - Q_4, \varphi_{13,14} = Q_4,$$

$$\varphi_{14,14} = -Q_4 - Q_4^T, \quad \varphi_{15,15} = -\Lambda_1, \ \varphi_{16,16} = -\Lambda_2,$$

L= diag $(k_1^- k_1^+, \dots, k_n^- k_n^+)$,

R= diag $(\frac{k_1^- + k_1^+}{2}, \dots, \frac{k_n^- + k_n^+}{2})$.

Moreover, desired controller gain matrix is given as $K = S_1^{-1} X, M = S_2^{-1} Y$.

Proof. Consider the following general Lyapunov-Krasovski functional:

$$V(t) = V_1(t) + V_2(t) + V_3(t) + V_4(t) + V_5(t),$$

Where $V_1(t) = x^T(t)Px(t) + y^T(t)Qy(t)$,

$$V_2(t) = \rho_1 \int_{t-\rho_1}^t x^T(s)P_1 x(s)ds + \rho_2 \int_{t-\rho_2}^t y^T(s)P_2 y(s)ds$$

$$V_3(t) = \int_{t-\tau_1(t)}^t y^T(s)P_3 y(s)ds + \int_{t-\tau_1}^t y^T(s)P_4 y(s)ds + \int_{t-\tau_2}^t x^T(s)P_5 x(s)ds + \int_{t-\tau_3}^t x^T(s)P_6 x(s)ds + \int_{t-\tau_3}^t y^T(s)P_7 y(s)ds$$

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ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 20, April 2016

$$V_4(t) = \tau_1 \iint_{-\tau_1}^{0}\int_{t+s}^{t} \dot{y}^T(\mu)Q_1\dot{y}(\mu)d\mu ds + \tau_2 \iint_{-\tau_2}^{0}\int_{t+s}^{t} \dot{x}^T(\mu)Q_2\dot{x}(\mu)d\mu ds + \tau_3 \iint_{-\tau_3}^{0}\int_{t+s}^{t} \dot{x}^T(\mu)Q_3\dot{x}(\mu)d\mu ds + \tau_1 \iint_{-\tau_3}^{0}\int_{t+s}^{t} \dot{y}^T(\mu)Q_4\dot{y}(\mu)d\mu ds$$

$$V_5(t) = \tau_1 \iint_{-\tau_1(t)}^{0}\int_{t+s}^{t} \dot{y}^T(\mu)Q_5\dot{y}(\mu)d\mu ds$$

(∗)

Calculating the derivation of $V_1(t)$ along the solution of the system (4), we have

$\dot{V}_1(t) = 2x^T(t)P\dot{x}(t) + 2y^T(t)Q\dot{y}(t)$ (5)

$\dot{V}_2(t) = \rho_1 x^T(t)Px(t) - \rho_1 x^T(t-\rho_1)P_1x(t-\rho_1) + \rho_2 y^T(t)P_2y(t)--\rho_2 y^T(t-\rho_2)P_2y(t-\rho_2)$ (6)

$$\dot{V}_3(t) \le y^T(t)P_3y(t) - y^T(t-\tau_1(t))P_3y(t-\tau_1(t))(1-\tau) + y^T(t)P_4y(t) - y^T(t-\tau_1)P_4y(t-\tau_1) + x^T(t)P_5x(t) - x^T(t-\tau_2)P_5x(t-\tau_2) + x^T(t)P_6x(t) - x^T(t-\tau_3)P_6x(t-\tau_3) + y^T(t)P_7y(t) - y^T(t-\tau_3)P_7y(t-\tau_3)$$

(7)

$$\dot{V}_4(t) = \tau_1^2\dot{y}^T(t)Q_1\dot{y}(t) - \tau_1\int_{t-\tau_1}^{t} \dot{y}^T(\mu)Q_1\dot{y}(\mu)d\mu + \tau_2^2\dot{x}^T(t)Q_2\dot{x}(t) - \tau_2\int_{t-\tau_2}^{t} \dot{x}^T(\mu)Q_2\dot{x}(\mu)d\mu + \tau_3^2\dot{x}^T(t)Q_3\dot{x}(t) - \tau_3\int_{t-\tau_3}^{t} \dot{x}^T(\mu)Q_3\dot{x}(\mu)d\mu + \tau_3^2\dot{y}^T(t)Q_4\dot{y}(t) - \tau_3\int_{t-\tau_3}^{t} \dot{y}^T(\mu)Q_4\dot{y}(\mu)d\mu$$ (8)

$$\dot{V}_5(t) = \tau_1\int_{-\tau_1(t)}^{0} \dot{y}^T(t)Q_5\dot{y}(t)ds - \tau_1\int_{-\tau_1(t)}^{0} \dot{y}^T(t+s)Q_5\dot{y}(t+s)ds - \tau_1\int_{t-\tau_1(t)}^{0} \dot{y}^T(t)Q_5\dot{y}(t)ds$$ (9)

By Lemma 1 and assumption H_2, we have

$$-\tau_1\int_{t-\tau_1}^{t} \dot{y}^T(\mu)Q_1\dot{y}(\mu)d\mu = -\tau_1\int_{t-\tau_1}^{t-\tau_1(t)} \dot{y}^T(\mu)Q_1\dot{y}(\mu)d\mu - \tau_1\int_{t-\tau_1(t)}^{t} \dot{y}^T(\mu)Q_1\dot{y}(\mu)d\mu$$

$$\le -\begin{bmatrix} y(t-\tau_1(t)) \\ y(t-\tau_1)\end{bmatrix}^T\begin{bmatrix} Q_1 & -Q_1 \\ * & Q_1\end{bmatrix}\begin{bmatrix} y(t-\tau_1(t)) \\ y(t-\tau_1)\end{bmatrix} - \begin{bmatrix} y(t) \\ y(t-\tau_1(t))\end{bmatrix}^T\begin{bmatrix} Q_1 & -Q_1 \\ * & Q_1\end{bmatrix}\begin{bmatrix} y(t) \\ y(t-\tau_1(t))\end{bmatrix}$$

Similarly find other integral terms. In addition

$0=2[x^T(t)+\dot{x}^T(t)]S_1[-\dot{x}(t)+\dot{x}(t)] = 2[x^T(t)+\dot{x}^T(t)]S_1 [-\dot{x}(t) - Ax(t-\rho_1) + Wg(y(t-\tau_1(t))) + Kx(t-\tau_3(t))]$

$$= -2x^T(t)S_1\dot{x}(t) - 2x^T(t)S_1Ax(t-\rho_1) + 2x^T(t)S_1 \times Wg(y(t-\tau_1)) + 2x^T(t)S_1Kx(t-\tau_3(t)) - 2\dot{x}^T(t)S_1 \times \dot{x}(t) - 2\dot{x}^T(t)S_1Ax(t-\rho_1) + 2\dot{x}^T(t)S_1Wg(y(t-\tau_1)) + 2\dot{x}^T(t)S_1Kx(t-\tau_3(t))$$

Similarly find 'y' term. For any positive-definite matrices Λ_1, Λ_2 the following inequalities hold. The proof can be found in [19, 21]:

$$\begin{bmatrix} y(t) \\ g(y(t))\end{bmatrix}^T\begin{bmatrix} -\Lambda_1 L & \Lambda_1 R \\ * & \Lambda_1\end{bmatrix}\begin{bmatrix} y(t) \\ g(y(t))\end{bmatrix} \ge 0$$ (17)

$$\begin{bmatrix} y(t-\sigma(t)) \\ g\left(y(t-\sigma(t))\right)\end{bmatrix}^T\begin{bmatrix} -\Lambda_2 L & \Lambda_2 R \\ * & \Lambda_2\end{bmatrix}\begin{bmatrix} y(t-\sigma(t)) \\ g\left(y(t-\sigma(t))\right)\end{bmatrix} \ge 0\,.$$ (18)

From (6) to (18), we have $\dot{V}(t) \le \xi^T(t)\phi\xi(t)$, (19)

Where ϕ is defined in (5) and

$$\xi^T = [x^T(t), x^T(t-\rho_1), x^T(t-\tau_2), x^T(t-\tau_2(t)), x^T(t-\tau_3), x^T(t-\tau_3(t)), y^T(t), \dot{y}^T(t), y^T(t-\rho_2), y^T(t-\tau_1), y^T(t-\tau_1(t)), y^T(t-\tau_3), g^T(y(t)), g^T(y(t-\tau_3(t)))].$$ (20)

Which implies $\dot{V}(t) \le 0$.It is easy to prove $\dot{V}(t) = 0$ iff

x(t)=y(t)=0.

On the other hand, from (∗) and theorem (1) conditions, we note that,

$$V_1(t_k, x(t_k), j) - V_1(t_k^-, x(t_k^-), i)$$

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Vol. 3, Special Issue 20, April 2016

$$= x_m^T(t_k)P_j x_m(t_k) - x_m^T(t_k^-)P_i x_m(t_k^-)$$
$$= x_m^T(t_k^-)D_{ik}P_j D_{ik}x_m(t_k^-) - x_m^T(t_k^-)P_i x_m(t_k^-)$$
$$= x_m^T(t_k^-)(D_{ik}P_j D_{ik} - P_i)\, x_m(t_k^-)$$
$$V_1(t_k, x(t_k), j) \le V_1(t_k^-, x(t_k^-), i) \quad (21)$$

Which implies that

$$V_1(t_k, x(t_k), j) \le V_1(t_k^-, x(t_k^-), i), \quad k \in Z_+ \quad (22)$$

According to the Lyapunov stability theory, the GRNs (4) are asymptotically stable. The proof is completed.

IV NUMERICAL EXAMPLE

In this section, an example is given to demonstrate the feasibility and efficiency of our theoretic results.

Example 4.1 Consider the genetic regulatory networks

$$\begin{cases} \dot{m}_i(t) = -Am(t-\rho_1) + Wf(p(t-\tau_1(t)) + I, \\ \dot{p}_i(t) = -Cp(t-\rho_2) + Dm(t-\tau_2(t)), \end{cases}$$

Where $A=\begin{bmatrix}9 & 0\\ 0 & 8\end{bmatrix}$, $W=\begin{bmatrix}-1.5 & 0\\ 1 & 2\end{bmatrix}$,
$C=\begin{bmatrix}8 & 0\\ 0 & 9\end{bmatrix}$, $D=\begin{bmatrix}-0.9 & 0\\ 0 & 9\end{bmatrix}$, $I=\begin{bmatrix}1\\ 2\end{bmatrix}$, $f=[f_1 \quad f_2]^T$,
$f(s) = \frac{s^2}{(1+s^2)}$, $\tau_1(t) = 0.01|\sin t|$, $\tau_2(t) = 0.01|\cos t|$.
When $\rho_1 = \rho_2 = [0.2 \quad 0.2]^T, k_i^+ = 0.65, k_i^- = 0$,
R= diag[0.325 0.325], L=diag [0 0].

The sampling period is taken as $\tau = 0.01$. Solving LMIs (a),
We obtain the following feasible solution, due to the length of the paper we have not provided all the solution here.

$$P = \begin{bmatrix}0.3384 & 0.0297\\ 0.0297 & 0.3799\end{bmatrix}, Q = \begin{bmatrix}32.2522 & 4.0331\\ 4.0331 & 50.4246\end{bmatrix},$$

$$S_1 = \begin{bmatrix}0.0071 & 0.0007\\ 0.0007 & 0.0097\end{bmatrix}, S_2 = \begin{bmatrix}0.0081 & 0.0004\\ 0.0004 & 0.0102\end{bmatrix},$$

$$X=\begin{bmatrix}-0.3439 & -0.0312\\ -0.0311 & -0.3851\end{bmatrix}, Y=\begin{bmatrix}-0.3765 & -0.0258\\ -0.0259 & -0.5085\end{bmatrix}$$

The gain matrices of the designed controller can be obtained as follows:

$$K=S_1^{-1}X = \begin{bmatrix}-48.5668 & 0.7458\\ 0.6336 & -48.9883\end{bmatrix},$$

$$M=S_2^{-1}Y = \begin{bmatrix}-46.4711 & -0.8717\\ -0.8318 & -49.8324\end{bmatrix},$$

This means that all conditions in Theorem 3.1 are satisfied. By Theorem 3.1, the system (1) is asymptotically stable under the given sampled-data control.

V CONCLUSIONS

In this paper, we have dealt with the stabilization problem of GRNs with leakage delays and impulses. Here we have considered the problem of how to stabilize the system by using sampled-data control strategy. Further some sufficient conditions were derived by a suitable Lyapunov function and input delay method. Finally, a numerical example has been given to show the effectiveness of our theoretic results.

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ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 20, April 2016

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