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A new complex network model and convergence dynamics for reputation computation in virtual organizations ☆

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Abstract

In this Letter, a new complex network model is established for reputation computation in virtual organizations, and its dynamics is investigated. Several sufficient conditions have been derived to ensure the global asymptotical stability of the new complex network model by using Lyapunov method and linear matrix inequality (LMI) technique, where the stability means that the reputation degrees of entities can tend to some fixed constants as time evolves. Also, for this new model, some other dynamical phenomena such as bifurcation and chaos synchronization are proposed for our consideration in the future. This may open a new research branch in the area.

Keywords: Complex network; Reputation computation; Virtual organization; Lyapunov method; Trust; Reputation degree; LMI; Convergence dynamics; Stability; Semantic web; Semantic grid

1. Introduction

The next generation of the internet is called the semantic web or semantic grid [1–3], which provides an environment that allows more intelligent knowledge management and data mining. The semantic web or semantic grid is becoming popular for sharing information and resources over the internet through web services or grid services, which are being developed based on the semantic grid [4,5]. Semantic grid allows anyone around the world to develop their own tools to interact with the resources on semantic grid easily. A virtual organization (VO) is a collection of users in the same administrative domain. A user can belong to many virtual organizations and has a different role (user, client, administrator and so on) in each of them. The main problem in virtual organization is its security, which includes how to identify a user and how to evaluate the actions that a user can perform. Virtual organizations [6,7], which allow access to large amount of computing resources, have become increasingly popular. The real and specific problem that underlies the grid concept is to coordinate resources-sharing and problem-solving dynamically among multi-institutional virtual organizations. The sharing that we are concerned with is not primarily files exchange, but rather, direct access to computers, software, data, and other resources, as is required by a range of collaborative problem-solving and resource-brokering strategies emerging in industry, engineering, and technology. For implementing secure and reliable high-performance computing services, it is necessary to know how to support the security infrastructure for virtual organizations. Security in virtual organizations [8–10] has attracted increasing attentions from various research communities in recent years due to the unique ability of marshalling collections of heterogeneous computers and resources, enabling easy access to diverse resources and services that

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otherwise could not be possible without a good computational model. However, the concept of virtual organizations does introduce its own set of security challenges, as users and resource providers can come from mutually distributed administrative domains and some participants can behave maliciously. These malicious attacks can generally compromise the resource provider node and the shared resources node may be malicious or compromised to harm the user's job running on the supporting platform.

Recently, in [10], the reputation has been recognized as an important factor for security of virtual organization. However, to the best of our knowledge, no models have been given for integrating computational systems into virtual organizations. In this Letter we establish a new complex network model for the reputation computation of virtual organizations.

It is well known that complex networks (which include world wide web, food webs, telephone call graphs, electrical power grids, neural networks, co-authorship and citation networks of scientists, cellular and metabolic networks, etc.) exist in all fields of sciences and humanities, and have been intensively studied [11–14]. Some properties of real-world complex networks can be well understood by considering internal interactions or coupling of the network, and their basic properties are mainly determined by the way of the connections among the nodes. Based on sound reasoning or evidence, we can use complex network model to study the reputation degrees for virtual organizations. Recently, in [15,16], the authors studied a dynamical complex network model and also discussed its synchronization. For the concerned issue of synchronization, there exist some recent publications, refer to [17–28]. In this Letter, we will try to propose a new complex network model for solving the problem of reputation computation in virtual organizations.

2. Preliminaries and model formulation

In order to establish a new model for reputation computation in virtual organizations, the concept of trust and reputation [29] are introduced.

The notion of trust is a complex subject relating to a firm belief in attributes such as reliability, honesty, and competence of the trusted entity. Here, we use the definition of the trust from [29]:

Definition 1. *Trust* is the firm belief in the competence of an entity to act as expected such that this firm belief is not a fixed value associated with the entity but rather it is subject to the entity's behavior and applies only within a specific context at a given time.

That is, the firm belief is a dynamic value and spans over a set of values ranging from very trustworthy to every untrustworthy. The trust level is built on past experiences, given for a specific context and specified for a given time because the trust level today between two entities may not be necessarily the same trust lever a year ago.

When making trust-based decisions, entities can rely on others for information pertaining to a specific entity. For example, if entity x wants to make a decision whether to have a transaction with entity y, which is unknown to x, then x can rely on the reputation of y. The definition of reputation that we will use is also introduced in [29] as follows:

Definition 2. The *reputation* of an entity is an expectation of its behavior based on other entities' observations or the collective information about the entity's past behavior within a specific context at a given time.

Now we try to establish a new complex network model for computing reputation degrees in virtual organizations. In [15,16] a complex dynamical network, which consists of N linearly and diffusively coupled identical nodes, is considered with each node being an n-dimensional dynamical system of the form:

$$\dot{x}_i(t) = f\big(x_i(t)\big) + c \sum_{j=1, j\neq i}^{N} G_{ij}\Gamma\big(x_j(t) - x_i(t)\big), \quad i = 1, 2, \ldots, N, \tag{1}$$

where $x_i(t) = (x_{i1}(t), x_{i2}(t), \ldots, x_{in}(t))^T \in \mathbb{R}^n$ is the state vector representing the state vectors of node i, $i = 1, 2, \ldots, N$, $f : \mathbb{R}^n \to \mathbb{R}^n$ is continuously differentiable, the constant c is the coupling strength, $\Gamma = \mathrm{diag}(\gamma_1, \gamma_2, \ldots, \gamma_n) \in \mathbb{R}^{n\times n}$ is a constant 0–1 matrix linking the coupled variables with $\gamma_i = 1$ for a specific i and $\gamma_j = 0$ $(j \neq i)$, that is, there is only one 1 in the diagonal of matrix Γ and all the other components of Γ are zeros, $G = (G_{ij})_{N\times N}$ is the coupling configuration matrix representing the coupling strengths and topological structure of the network, in which G_{ij} is defined as follows: if there is a connection from node i to node j $(j \neq i)$, then the elements of coupling matrix $G_{ij} = G_{ji} = 1$; otherwise, $G_{ij} = G_{ji} = 0$ $(j \neq i)$, and the diagonal elements of matrix G are defined by

$$G_{ii} = -\sum_{j=1, j\neq i}^{N} G_{ij} = -\sum_{j=1, j\neq i}^{N} G_{ji}. \tag{2}$$

Then, in this case, the complex network (1) reduces to the model

$$\dot{x}_i(t) = f\big(x_i(t)\big) + c\sum_{j=1}^{N} G_{ij}\Gamma x_j(t), \quad i = 1, 2, \ldots, N. \tag{3}$$

Hereafter, suppose that the network (3) is connected in the sense that there are no isolated clusters, so the coupling configuration G is an irreducible matrix.

In [25], a time-varying coupling was introduced into the complex network model, thus the network (3) can be extended as:

$$\dot{x}_i(t) = f\big(x_i(t)\big) + \sum_{j=1}^{N} G_{ij}(t)A(t)x_j(t), \quad i = 1, 2, \ldots, N. \tag{4}$$

As a special case, the coupling linking matrix $A(t)$ can be a constant 0–1 matrix in the form $\Gamma = \mathrm{diag}(\gamma_1, \gamma_2, \ldots, \gamma_n) \in \mathbb{R}^{n\times n}$ and the coupling configuration matrix $G(t) = c(G_{ij})_{N\times N}$ for all time t, where c is a constant and G_{ij} satisfies the following condition: if there is a connection between node i and node j $(i \neq j)$, then $G_{ij} = G_{ji} = 1$; otherwise, $G_{ij} = G_{ji} = 0$ $(j \neq i)$. Then, in this case, the time-varying network (4) reduces to the model (3).

It is noted that most of the real-world complex dynamical networks are time-varying evolving networks, which implies that the coupling configuration matrix $G(t) = (G_{ij}(t))_{N\times N}$ and the inner coupling matrix $A(t) = (a_{ij}(t))_{N\times N}$ are functions with respect to time t. Moreover, real-world complex dynamical networks may be directed networks, such as WWW, whose coupling configuration $G(t)$ is not symmetric.

Although model (3) reflects the complexity from the structure of networks, it is a simple uniform dynamical network without time-varying or delay coupling. Considering the existence of delays in spreading due to the finite speeds of transmission as well as traffic congestions, so it is inevitable that time delays should be modelled or introduced for simulating more realistic networks. In [24], the following complex dynamical network model with delay coupling is formulated:

$$\dot{x}_i(t) = f\big(x_i(t)\big) + c\sum_{j=1}^{N} G_{ij}\Gamma x_j(t-\tau), \quad i = 1, 2, \ldots, N, \tag{5}$$

where τ is a time delay. As the coupling matrix G is irreducible, symmetric, all the off-diagonal elements of G are nonnegative and satisfying (2), in [24–26], the local stability or local synchronization has been studied via linearized technique. In [20,21], a distance between any point and synchronization manifold is defined, which was used to discuss global convergence for complete regular coupling configuration, and a synchronization scheme is considered for an array of linearly coupled dynamical systems. In [17–19], the global asymptotical synchronization is investigated for the following complex network of the form:

$$\dot{x}_i(t) = -Cx_i(t) + Af\big(x_i(t)\big) + Bf\big(x_i(t-\tau)\big) + I(t) + c\sum_{j=1}^{N} G_{ij}\Gamma x_j(t), \quad i = 1, 2, \ldots, N, \tag{6}$$

where $C = \mathrm{diag}(c_1, c_2, \ldots, c_n) \in \mathbb{R}^{n\times n}$ is a diagonal matrix with positive diagonal entries $c_i > 0$, $i = 1, 2, \ldots, n$, $A = (a_{ij})_{n\times n}$ and $B = (b_{ij})_{n\times n}$ are weight and delayed weight matrices, respectively, $I(t) = (I_1(t), I_2(t), \ldots, I_n(t))^T \in \mathbb{R}^n$ is the external input vector, $\Gamma = \mathrm{diag}(\gamma_1, \gamma_2, \ldots, \gamma_n) \in \mathbb{R}^{n\times n}$, $f(x_i(t)) = (f_1(x_{i1}(t)), f_2(x_{i2}(t)), \ldots, f_n(x_{in}(t)))^T \in \mathbb{R}^n$ are the activation functions of the nodes.

Equivalently, the system (6) can be written as:

$$\begin{aligned}\dot{x}_{ik}(t) &= -c_k x_{ik}(t) + \sum_{l=1}^{n} a_{kl} f_l\big(x_{il}(t)\big) + \sum_{l=1}^{n} b_{kl} f_l\big(x_{il}(t-\tau)\big) + I_k(t) + c\sum_{j=1}^{N} G_{ij}\gamma_k x_{jk}(t),\\ &\quad i = 1, 2, \ldots, N; \quad k = 1, 2, \ldots, n.\end{aligned} \tag{7}$$

Based on above discussions and descriptions, to formulate or compute the reputation degrees in virtual organizations, we propose a new model of the following array of N nonlinearly coupled complex network model of the type:

$$\begin{aligned}\dot{x}_i(t) &= -Cx_i(t) + Af\big(x_i(t)\big) + B\int_{-\infty}^{t} K(t-s)f\big(x_i(s)\big)\,ds + I_i\\ &\quad + \sum_{j=1, j\neq i}^{N} d_{ij}\left[\Gamma\big(g\big(x_j(t)\big) - g\big(x_i(t)\big)\big) + \Lambda\left(\int_{-\infty}^{t} K(t-s)g\big(x_j(s)\big)\,ds - \int_{-\infty}^{t} K(t-s)g\big(x_i(s)\big)\,ds\right)\right],\\ &\quad i = 1, 2, \ldots, N,\end{aligned} \tag{8}$$

or equivalently,

$$\dot{x}_{ik}(t) = -c_k x_{ik}(t) + \sum_{l=1}^{n} a_{kl} f_l\big(x_{il}(t)\big) + \sum_{l=1}^{n} b_{kl} \int_{-\infty}^{t} K_l(t-s) f_l\big(x_{il}(s)\big)\,ds + I_{ik}$$
$$+ \sum_{j=1}^{N} d_{ij}\left[\gamma_k\big(g_k\big(x_{jk}(t)\big) - g_k\big(x_{ik}(t)\big)\big) + \lambda_k\left(\int_{-\infty}^{t} K_k(t-s) g_k\big(x_{jk}(s)\big)\,ds - \int_{-\infty}^{t} K_k(t-s) g_k\big(x_{ik}(s)\big)\,ds\right)\right],$$
$$i = 1,2,\ldots,N; \quad k = 1,2,\ldots,n, \tag{9}$$

where $x_i(t) = (x_{i1}(t), x_{i2}(t), \ldots, x_{in}(t))^T \in \mathbb{R}^n$ is the state vector of the ith node of the network, $i = 1,2,\ldots,N$, $C = \mathrm{diag}(c_1, c_2, \ldots, c_n) \in \mathbb{R}^{n\times n}$ is a diagonal matrix with positive diagonal entries $c_i > 0$, $i = 1,2,\ldots,n$, $A = (a_{ij})_{n\times n}$ and $B = (b_{ij})_{n\times n}$ are weight and delayed weight matrices, respectively, $f(x_i(t)) = (f_1(x_{i1}(t)), f_2(x_{i2}(t)), \ldots, f_n(x_{in}(t)))^T \in \mathbb{R}^n$ and $g(x_j(t)) = (g_1(x_{j1}(t)), g_2(x_{j2}(t)), \ldots, g_n(x_{jn}(t)))^T \in \mathbb{R}^n$ represent the output of the node i and j, respectively, $I_i = (I_{i1}, I_{i2}, \ldots, I_{in})^T \in \mathbb{R}^n$ is an external input vector, $\Gamma = \mathrm{diag}(\gamma_1, \gamma_2, \ldots, \gamma_n) \in \mathbb{R}^{n\times n}$ and $\Lambda = \mathrm{diag}(\lambda_1, \lambda_2, \ldots, \lambda_n) \in \mathbb{R}^{n\times n}$ are diagonal matrices, which implies that the rth state variable of the ith node of the network is only affected by the rth state variables of the other nodes of the networks, and the weight function $K(t) = \mathrm{diag}(K_1(t), K_2(t), \ldots, K_n(t)) \in \mathbb{R}^{n\times n}$ is a nonnegative bounded function defined on $[0, +\infty)$ reflecting the influence of the past states on the current dynamics, and the coupling matrix $D = (d_{ij})_{N\times N}$ is the coupling configuration matrix representing the coupling strengths and topological structure of the network, in which d_{ij} is defined as follows: if there is a connection from node i to node j $(j \neq i)$, then the coupling strength $d_{ij} \in [0,1]$, and the diagonal elements of matrix D is defined similarly as (2) by

$$d_{ii} = -\sum_{j=1, j\neq i}^{N} d_{ij}. \tag{10}$$

The coupled complex network model (8) can be rewritten as:

$$\dot{x}_i(t) = -Cx_i(t) + Af\big(x_i(t)\big) + B\int_{-\infty}^{t} K(t-s) f\big(x_i(s)\big)\,ds + I_i + \sum_{j=1}^{N} d_{ij}\left[\Gamma g\big(x_j(t)\big) + \Lambda \int_{-\infty}^{t} K(t-s) g\big(x_j(s)\big)\,ds\right],$$
$$i = 1,2,\ldots,N, \tag{11}$$

or equivalently,

$$\dot{x}_{ik}(t) = -c_k x_{ik}(t) + \sum_{l=1}^{n} a_{kl} f_l\big(x_{il}(t)\big) + \sum_{l=1}^{n} b_{kl} \int_{-\infty}^{t} K_l(t-s) f_l\big(x_{il}(s)\big)\,ds + I_{ik}$$
$$+ \sum_{j=1}^{N} d_{ij}\left[\gamma_k g_k\big(x_{jk}(t)\big) + \lambda_k \int_{-\infty}^{t} K_k(t-s) g_k\big(x_{jk}(s)\big)\,ds\right], \quad i = 1,2,\ldots,N; \quad k = 1,2,\ldots,n. \tag{12}$$

In fact, the proposed complex model (8) can describe the dynamical evolution of the reputation for virtual organizations, in which let $x_i(t)$ denote the reputation degree of the ith entity at time t, $x_{ij}(t)$ $(j = 1,2,\ldots,n)$ be the jth index of the reputation degree $x_i(t)$, C, A, B be the inner coupling matrices, where C is the restraint of the reputation degree, A is the weight matrix representing the influence of the present reputation degree and B is the weight matrix representing the influence of the past reputation degree. Also, let I be the external influence, the coupling configuration matrix D describe the interaction between entities, Γ be the weight matrix of the influence of other entities's reputation degree compared to a certain entity's own reputation degree at present time, and Λ be the weight matrix of the influence of other entities's past reputation degree compared to a certain entity's own past reputation degree, assume that Γ and Λ are the diagonal matrices for simplicity which imply that the index of the reputation degree of each entity is mostly influenced by the same indexes of the other entities.

From new model (8), one can see that the reputation degree that an entity holds is based on its own present reputation degree, past reputation degree, and the relationships with other entities as well as their reputation degrees and past reputation degrees.

Now we define several special kernel matrix functions $K(\cdot)$.

Let

$$K_i(s) = \delta(s-\tau), \quad \tau > 0, \quad i = 1,2,\ldots,n, \tag{13}$$

where $\delta(\cdot)$ is the Dirac function, then the system (11) can be written as:

$$\dot{x}_i(t) = -Cx_i(t) + Af\big(x_i(t)\big) + Bf\big(x_i(t-\tau)\big) + I_i + \sum_{j=1}^{N} d_{ij}\big[\Gamma g\big(x_j(t)\big) + \Lambda g\big(x_j(t-\tau)\big)\big], \quad i = 1, 2, \ldots, N, \tag{14}$$

which is a model of delay coupling.
Let

$$K_i(s) = \begin{cases} 0, & s \geqslant \tau, \\ 1, & s < \tau, \end{cases} \quad i = 1, 2, \ldots, n, \tag{15}$$

where τ is a positive constant, then the model (11) can be written as:

$$\dot{x}_i(t) = -Cx_i(t) + Af\big(x_i(t)\big) + B\int_{t-\tau}^{t} K(t-s)f\big(x_i(s)\big)\,ds + I + \sum_{j=1}^{N} d_{ij}\left[\Gamma g\big(x_j(t)\big) + \Lambda \int_{t-\tau}^{t} K(t-s)g\big(x_j(s)\big)\,ds\right], \\ i = 1, 2, \ldots, N, \tag{16}$$

which implies that the long-term past reputation degree of an entity is not considered. Also, $K_i(\cdot)$ could be a decaying function, which is decreasing with the time variable, such as

$$K_i(s) = \alpha e^{-\alpha s}, \quad \alpha > 0, \quad i = 1, 2, \ldots, n, \tag{17}$$

which satisfies

$$\int_{0}^{+\infty} K_i(s)\,ds = 1, \quad i = 1, 2, \ldots, n. \tag{18}$$

For this new model (11), there are some interesting dynamical phenomena such as stability, synchronization, bifurcation and chaos. As a start on this new model, here we only discuss its stability which implies the reputation degree of all entities tend to some fixed constants. Also, chaos means that the reputation degree of entities are random and changeable, which will be discussed in the near future.

We impose the following assumption:

(A_1) $f_i(\cdot), g_j(\cdot)$ $(i, j = 1, 2, \ldots, n)$ are nondecreasing and Lipschitz continuous; that is, there exist constants F_i, G_j such that

$$\big|f_i(x) - f_i(y)\big| \leqslant F_i|x-y|, \qquad |g_j(x) - g_j(y)| \leqslant G_j|x-y| \quad \forall x, y \in \mathbb{R}. \tag{19}$$

Assume that the model (16) has an equilibrium $x^* = (x_1^*, x_2^*, \ldots, x_N^*)$ for a given I. To simplify the proofs, we shift the equilibrium point x^* of (16) to the origin. Using the following transformation

$$y_i(t) = x_i(t) - x_i^*, \quad i = 1, 2, \ldots, N.$$

The model (16) can be transformed into the following form:

$$\dot{y}_i(t) = -Cy_i(t) + Ah\big(y_i(t)\big) + B\int_{t-\tau}^{t} K(t-s)h\big(y_i(s)\big)\,ds + \sum_{j=1}^{N} d_{ij}\left[\Gamma l\big(y_j(t)\big) + \Lambda \int_{t-\tau}^{t} K(t-s)l\big(y_j(s)\big)\,ds\right], \\ i = 1, 2, \ldots, N, \tag{20}$$

where $h(y_i(t)) = (h_1(y_{i1}(t)), h_2(y_{i2}(t)), \ldots, h_n(y_{in}(t)))^T \in \mathbb{R}^n$, $h(y_i(t)) = f(y_i(t) + x_i^*) - f(x_i^*)$, $h(0) = 0$ and $l(y_i(t)) = (l_1(y_{i1}(t)), l_2(y_{i2}(t)), \ldots, l_n(y_{in}(t)))^T \in \mathbb{R}^n$, $l(y_i(t)) = g(y_i(t) + x_i^*) - g(x_i^*)$, $l(0) = 0$ $(i = 1, 2, \ldots, N)$. Moreover, from (19), we know that

$$\big|h_k(y_{ik})\big| \leqslant F_k|y_{ik}| \quad \forall y_{ik} \in \mathbb{R}, \quad i = 1, 2, \ldots, N, \quad k = 1, 2, \ldots, n, \tag{21}$$

$$\big|l_k(y_{ik})\big| \leqslant G_k|y_{ik}| \quad \forall y_{ik} \in \mathbb{R}, \quad i = 1, 2, \ldots, N, \quad k = 1, 2, \ldots, n. \tag{22}$$

In this Letter, the following two elementary lemmas are needed:

Lemma 1 *(Schur complement [30]). The following linear matrix inequality (LMI)*

$$\begin{pmatrix} Q(x) & S(x) \\ S(x)^T & R(x) \end{pmatrix} > 0,$$

where $Q(x) = Q(x)^T$, $R(x) = R(x)^T$, is equivalent to one of the following conditions:

(i) $Q(x) > 0$, $R(x) - S(x)^T Q(x)^{-1} S(x) > 0$,
(ii) $R(x) > 0$, $Q(x) - S(x) R(x)^{-1} S(x)^T > 0$.

Lemma 2 *(Jensen inequality [31]). For any constant matrix $W \in \mathbb{R}^{m\times m}$, $W = W^T$, scalar $r > 0$, vector function ω: $[0, r] \in \mathbb{R}^{m\times m}$ such that the integrations concerned are well defined, then*

$$r\int_0^r \omega(s)W\omega(s)\,ds \geqslant \left(\int_0^r \omega(s)\,ds\right)^T W\left(\int_0^r \omega(s)\,ds\right).$$

3. Stability in the complex network model

In this section, several new global stability criteria are derived for the complex network (20) satisfying (17), which means that the long-term past reputation degrees of entities are not under consideration.

To simplify the proof, we give some notations, let $A \otimes B$ denote the Kronecker product of matrices A and B, let

$$\bar{C} = E_N \otimes C, \qquad \bar{A} = E_N \otimes A, \qquad \bar{B} = E_N \otimes B, \qquad \bar{\Gamma} = D \otimes \Gamma, \qquad \bar{\Lambda} = D \otimes \Lambda, \qquad \bar{K} = E_N \otimes K, \tag{23}$$

$$y_i(t) = \big(y_{i1}(t), y_{i2}(t), \ldots, y_{in}(t)\big)^T, \quad \forall i = 1, 2, \ldots, N, \tag{24}$$

$$y(t) = \big(y_1^T(t), y_2^T(t), \ldots, y_N^T(t)\big)^T, \tag{25}$$

$$\bar{h}\big(y(t)\big) = \big(h^T\big(y_1(t)\big), h^T\big(y_2(t)\big), \ldots, h^T\big(y_N(t)\big)\big)^T, \tag{26}$$

$$\bar{l}\big(y(t)\big) = \big(l^T\big(y_1(t)\big), l^T\big(y_2(t)\big), \ldots, l^T\big(y_N(t)\big)\big)^T, \tag{27}$$

where E_N is the N-dimensional identity matrix.

Then the complex network (20) can be rewritten as

$$\dot{y}(t) = -\bar{C}y(t) + \bar{A}\bar{h}\big(y(t)\big) + \bar{B}\int_{t-\tau}^{t} \bar{K}(t-s)\bar{h}\big(y(s)\big)\,ds + \bar{\Gamma}\bar{l}\big(y(t)\big) + \bar{\Lambda}\int_{t-\tau}^{t} \bar{K}(t-s)\bar{l}\big(y(s)\big)\,ds, \quad i = 1, 2, \ldots, N. \tag{28}$$

Theorem 1. *Under assumption* (A_1)*, the equilibrium point of model (28) is globally asymptotically stable if there are positive definite diagonal matrices $\bar{H} = \mathrm{diag}(\bar{H}_1, \bar{H}_2, \ldots, \bar{H}_{Nn}) \in \mathbb{R}^{Nn\times Nn}$, $\bar{J} = \mathrm{diag}(\bar{J}_1, \bar{J}_2, \ldots, \bar{J}_{Nn}) \in \mathbb{R}^{Nn\times Nn}$, and positive definite matrices $\bar{P} = (\bar{p}_{ij})_{Nn\times Nn}$, $\bar{Q} = (\bar{q}_{ij})_{Nn\times Nn}$, $\bar{R} = (\bar{r}_{ij})_{Nn\times Nn}$, such that*

$$N = \begin{pmatrix} -2\bar{P}\bar{C} & \bar{P}\bar{A} + \bar{F}\bar{H} & \bar{P}\bar{B} & \bar{P}\bar{\Gamma} + \bar{G}\bar{J} & \bar{P}\bar{\Lambda} \\ \bar{A}^T\bar{P} + \bar{H}\bar{F} & \tau^2\bar{K}^T(0)\bar{Q}\bar{K}(0) - 2\bar{H} & 0 & 0 & 0 \\ \bar{B}^T\bar{P} & 0 & -\bar{Q} & 0 & 0 \\ \bar{\Gamma}^T\bar{P} + \bar{J}\bar{G} & 0 & 0 & \tau^2\bar{K}^T(0)\bar{R}\bar{K}(0) - 2\bar{J} & 0 \\ \bar{\Lambda}^T\bar{P} & 0 & 0 & 0 & -\bar{R} \end{pmatrix}, \tag{29}$$

where

$$F = \mathrm{diag}(F_1, F_2, \ldots, F_n) \in \mathbb{R}^{n\times n}, \qquad \bar{F} = E_N \otimes F, \qquad G = \mathrm{diag}(G_1, G_2, \ldots, G_n) \in \mathbb{R}^{n\times n}, \qquad \bar{G} = E_N \otimes G.$$

Proof. Consider the following Lyapunov functional:

$$V(t) = \sum_{i=1}^{i=3} V_i(t), \tag{30}$$

where

$$V_1(t) = y^T(t)\bar{P}y(t), \tag{31}$$

$$V_2(t) = \tau\int_{-\tau}^{0}\int_{t+s}^{t} \big(\bar{K}(t-\theta)\bar{h}\big(y(\theta)\big)\big)^T \bar{Q}\big(\bar{K}(t-\theta)\bar{h}\big(y(\theta)\big)\big)\,d\theta\,ds, \tag{32}$$

$$V_3(t) = \tau\int_{-\tau}^{0}\int_{t+s}^{t} \big(\bar{K}(t-\theta)\bar{l}\big(y(\theta)\big)\big)^T \bar{R}\big(\bar{K}(t-\theta)\bar{l}\big(y(\theta)\big)\big)\,d\theta\,ds, \tag{33}$$

where $\bar{P}=(\bar{p}_{ij})_{Nn\times Nn}$, $\bar{Q}=(\bar{q}_{ij})_{Nn\times Nn}$ and $\bar{R}=(\bar{r}_{ij})_{Nn\times Nn}$ are positive definite matrices.

Computing the derivative of $V(y)$ along the trajectory of system (28), we obtain

$$\begin{aligned}
\dot{V}_1(t)\big|_{(28)} &= 2y^T(t)\bar{P}\dot{y}(t)\\
&= -2y^T(t)\bar{P}\bar{C}y(t)+2y^T(t)\bar{P}\bar{A}\bar{h}\big(y(t)\big)+2y^T(t)\bar{P}\bar{B}\int_{t-\tau}^{t}\bar{K}(t-s)\bar{h}\big(y(s)\big)\,ds\\
&\quad +2y^T(t)\bar{P}\bar{\Gamma}\bar{l}\big(y(t)\big)+2y^T(t)\bar{P}\bar{\Lambda}\int_{t-\tau}^{t}\bar{K}(t-s)\bar{l}\big(y(s)\big)\,ds\\
&= -2y^T(t)\bar{P}\bar{C}y(t)+y^T(t)\bar{P}\bar{A}\bar{h}\big(y(t)\big)+\bar{h}^T\big(y(t)\big)\bar{A}^T\bar{P}y(t)+y^T(t)\bar{P}\bar{B}\int_{t-\tau}^{t}\bar{K}(t-s)\bar{h}\big(y(s)\big)\,ds\\
&\quad +\left(\int_{t-\tau}^{t}\bar{K}(t-s)\bar{h}\big(y(s)\big)\,ds\right)^T\bar{B}^T\bar{P}y(t)+y^T(t)\bar{P}\bar{\Gamma}\bar{l}\big(y(t)\big)+\bar{l}^T\big(y(t)\big)\bar{\Gamma}^T\bar{P}y(t)\\
&\quad +y^T(t)\bar{P}\bar{\Lambda}\int_{t-\tau}^{t}\bar{K}(t-s)\bar{l}\big(y(s)\big)\,ds+\left(\int_{t-\tau}^{t}\bar{K}(t-s)\bar{l}\big(y(s)\big)\,ds\right)^T\bar{\Lambda}^T\bar{P}y(t).
\end{aligned}\tag{34}$$

According to Lemma 2, we have

$$\begin{aligned}
\dot{V}_2(t)\big|_{(28)} &= \tau\int_{-\tau}^{0}\big(\bar{K}(0)\bar{h}\big(y(t)\big)\big)^T\bar{Q}\big(\bar{K}(0)\bar{h}\big(y(t)\big)\big)\,ds-\tau\int_{-\tau}^{0}\big(\bar{K}(-s)\bar{h}\big(y(t+s)\big)\big)^T\bar{Q}\big(\bar{K}(-s)\bar{h}\big(y(t+s)\big)\big)\,ds\\
&\quad +2\tau\int_{-\tau}^{0}\int_{t+s}^{t}\left(\frac{d\bar{K}(t-\theta)}{dt}\bar{h}\big(y(\theta)\big)\right)^T\bar{Q}\big(\bar{K}(t-\theta)\bar{h}\big(y(\theta)\big)\big)\,d\theta\,ds\\
&= \tau^2\bar{h}^T\big(y(t)\big)\bar{K}^T(0)\bar{Q}\bar{K}(0)\bar{h}\big(y(t)\big)-\tau\int_{t-\tau}^{t}\big(\bar{K}(t-s)\bar{h}\big(y(s)\big)\big)^T\bar{Q}\big(\bar{K}(t-s)\bar{h}\big(y(s)\big)\big)\,ds\\
&\quad -2\alpha\tau\int_{-\tau}^{0}\int_{t+s}^{t}\big(\bar{K}(t-\theta)\bar{h}\big(y(\theta)\big)\big)^T\bar{Q}\big(\bar{K}(t-\theta)\bar{h}\big(y(\theta)\big)\big)\,d\theta\,ds\\
&\leqslant \tau^2\bar{h}^T\big(y(t)\big)\bar{K}^T(0)\bar{Q}\bar{K}(0)\bar{h}\big(y(t)\big)-\left(\int_{t-\tau}^{t}\bar{K}(t-s)\bar{h}\big(y(s)\big)\,ds\right)^T\bar{Q}\left(\int_{t-\tau}^{t}\bar{K}(t-s)\bar{h}\big(y(s)\big)\,ds\right).
\end{aligned}\tag{35}$$

Similarly,

$$\dot{V}_3(t)\big|_{(28)} \leqslant \tau^2\bar{l}^T\big(y(t)\big)\bar{K}^T(0)\bar{R}\bar{K}(0)\bar{l}\big(y(t)\big)-\left(\int_{t-\tau}^{t}\bar{K}(t-s)\bar{l}\big(y(s)\big)\,ds\right)^T\bar{R}\left(\int_{t-\tau}^{t}\bar{K}(t-s)\bar{l}\big(y(s)\big)\,ds\right).\tag{36}$$

From assumption (A_1), it follows that

$$\bar{h}^T\big(y(t)\big)\bar{H}\bar{F}y(t)-\bar{h}^T\big(y(t)\big)\bar{H}\bar{h}\big(y(t)\big)\geqslant 0,\tag{37}$$

and

$$\bar{l}^T\big(y(t)\big)\bar{J}\bar{G}y(t)-\bar{l}^T\big(y(t)\big)\bar{J}\bar{l}\big(y(t)\big)\geqslant 0,\tag{38}$$

where

$$\begin{aligned}
&\bar{H}=\operatorname{diag}(\bar{H}_1,\bar{H}_2,\ldots,\bar{H}_{Nn})\in\mathbb{R}^{Nn\times Nn}, \qquad \bar{J}=\operatorname{diag}(\bar{J}_1,\bar{J}_2,\ldots,\bar{J}_{Nn})\in\mathbb{R}^{Nn\times Nn},\\
&F=\operatorname{diag}(F_1,F_2,\ldots,F_n)\in\mathbb{R}^{n\times n}, \qquad \bar{F}=E_N\otimes F,
\end{aligned}$$

$$G = \mathrm{diag}(G_1, G_2, \ldots, G_n) \in \mathbb{R}^{n\times n}, \qquad \bar{G} = E_N \otimes G$$

are positive definite diagonal matrices.

Combining (34)–(38), we obtain

$$\dot{V}(t)\big|_{(28)} \leqslant \eta^T N \eta, \tag{39}$$

where

$$\eta = \left(y^T(t), \bar{h}^T\big(y(t)\big), \left(\int_{t-\tau}^{t} \bar{K}(t-s)\bar{h}\big(y(s)\big)\,ds\right)^T, \bar{l}^T\big(y(t)\big), \left(\int_{t-\tau}^{t} \bar{K}(t-s)\bar{l}\big(y(s)\big)\,ds\right)^T\right)^T.$$

Therefore, from (39), we know that under the given condition (29), $\dot{V}(y(t)) = 0$ if and only if $y(t) = 0$, otherwise $\dot{V}(y(t)) \leqslant 0$. Moreover, on the other hand, $V(y)$ is radially unbounded since $V(y(t)) \to \infty$ as $\|y(t)\| \to \infty$. So we conclude that the equilibrium of (28) is globally asymptotically stable. This completes the proof. □

Note that the matrix given in condition (29) is a high dimension-matrix as the complex network is large (i.e., N is a large number). In the following, we give another theorem which only need to verify a lower dimension matrix-condition based on Lemma 1.

Theorem 2. *Under Assumption* (A_1)*, the equilibrium point of model* (28) *is globally asymptotically stable if there are positive definite diagonal matrices* $\bar{H} = \mathrm{diag}(\bar{H}_1, \bar{H}_2, \ldots, \bar{H}_{Nn}) \in \mathbb{R}^{Nn\times Nn}$*,* $\bar{J} = \mathrm{diag}(\bar{J}_1, \bar{J}_2, \ldots, \bar{J}_{Nn}) \in \mathbb{R}^{Nn\times Nn}$*, and positive definite matrices* $\bar{P} = (\bar{p}_{ij})_{Nn\times Nn}$*,* $\bar{Q} = (\bar{q}_{ij})_{Nn\times Nn}$*,* $\bar{R} = (\bar{r}_{ij})_{Nn\times Nn}$*, such that*

$$\begin{aligned}&-2\bar{P}\bar{C} - \big(\bar{A}^T\bar{P} + \bar{H}\bar{F}\big)\big(\tau^2\bar{K}^T(0)\bar{Q}\bar{K}(0) - 2\bar{H}\big)^{-1}\big(\bar{A}^T\bar{P} + \bar{H}\bar{F}\big)^T + \big(\bar{B}^T\bar{P}\big)\bar{Q}^{-1}\big(\bar{B}^T\bar{P}\big)^T\\&\quad - \big(\bar{\Gamma}^T\bar{P} + \bar{J}\bar{G}\big)\big(\tau^2\bar{K}^T(0)\bar{R}\bar{K}(0) - 2\bar{J}\big)^{-1}\big(\bar{\Gamma}^T\bar{P} + \bar{J}\bar{G}\big)^T + \big(\bar{\Lambda}^T\bar{P}\big)\bar{R}^{-1}\big(\bar{\Lambda}^T\bar{P}\big)^T < 0,\end{aligned} \tag{40}$$

$$\tau^2\bar{K}^T(0)\bar{Q}\bar{K}(0) - 2\bar{H} < 0, \tag{41}$$

$$\tau^2\bar{K}^T(0)\bar{R}\bar{K}(0) - 2\bar{J} < 0, \tag{42}$$

where

$$F = \mathrm{diag}(F_1, F_2, \ldots, F_n) \in \mathbb{R}^{n\times n}, \qquad \bar{F} = E_N \otimes F,$$
$$G = \mathrm{diag}(G_1, G_2, \ldots, G_n) \in \mathbb{R}^{n\times n}, \qquad \bar{G} = E_N \otimes G.$$

Proof. Let

$$Q = -2\bar{P}\bar{C}, \qquad S = (\bar{P}\bar{A} + \bar{F}\bar{H}, \bar{P}\bar{B}, \bar{P}\bar{\Gamma} + \bar{G}\bar{J}, \bar{P}\bar{\Lambda}),$$

and

$$R = \begin{pmatrix} \tau^2\bar{K}^T(0)\bar{Q}\bar{K}(0) - 2\bar{H} & 0 & 0 & 0\\ 0 & -\bar{Q} & 0 & 0\\ 0 & 0 & \tau^2\bar{K}^T(0)\bar{R}\bar{K}(0) - 2\bar{J} & 0\\ 0 & 0 & 0 & -\bar{R}\end{pmatrix}.$$

Using Lemma 1, one can see that the condition (29) is equivalent to conditions (40)–(42). This completes the proof. □

Moreover, we note that the dimension of condition (29) in Theorem 1 is higher than (40)–(42) in Theorem 2, but it is solvable using the LMI-toolbox in Matlab. The following theorem provides the tradeoff between the matrix-dimension and solving by LMI.

Theorem 3. *Under assumption* (A_1)*, the equilibrium point of model* (28) *is globally asymptotically stable if there are positive definite diagonal matrices* $\bar{H} = \mathrm{diag}(\bar{H}_1, \bar{H}_2, \ldots, \bar{H}_{Nn}) \in \mathbb{R}^{Nn\times Nn}$*,* $\bar{J} = \mathrm{diag}(\bar{J}_1, \bar{J}_2, \ldots, \bar{J}_{Nn}) \in \mathbb{R}^{Nn\times Nn}$*, and positive definite matrices* $\bar{P} = (\bar{p}_{ij})_{Nn\times Nn}$*,* $\bar{Q} = (\bar{q}_{ij})_{Nn\times Nn}$*,* $\bar{R} = (\bar{r}_{ij})_{Nn\times Nn}$*, such that*

$$N_1 = \begin{pmatrix} -\bar{P}\bar{C} & \bar{P}\bar{A} + \bar{F}\bar{H} & \bar{P}\bar{B}\\ \bar{A}^T\bar{P} + \bar{H}\bar{F} & \tau^2\bar{K}^T(0)\bar{Q}\bar{K}(0) - 2\bar{H} & 0\\ \bar{B}^T\bar{P} & 0 & -\bar{Q}\end{pmatrix} < 0, \tag{43}$$

$$N_2 = \begin{pmatrix} -\bar{P}\bar{C} & \bar{P}\bar{\Gamma} + \bar{G}\bar{J} & \bar{P}\bar{\Lambda}\\ \bar{\Gamma}^T\bar{P} + \bar{J}\bar{G} & \tau^2\bar{K}^T(0)\bar{R}\bar{K}(0) - 2\bar{J} & 0\\ \bar{\Lambda}^T\bar{P} & 0 & -\bar{R}\end{pmatrix} < 0, \tag{44}$$

where

$$F = \mathrm{diag}(F_1, F_2, \ldots, F_n) \in \mathbb{R}^{n\times n}, \qquad \bar{F} = E_N \otimes F,$$
$$G = \mathrm{diag}(G_1, G_2, \ldots, G_n) \in \mathbb{R}^{n\times n}, \qquad \bar{G} = E_N \otimes G.$$

Proof. Choose the same Lyapunov functional as in (30)–(33). Similar to (39), we can obtain

$$\begin{aligned}\dot{V}(t)|_{(28)} \leqslant{}& \left(y^T(t) \quad \bar{h}^T\big(y(t)\big) \quad \left(\int_{t-\tau}^{t} \bar{K}(t-s)\bar{h}\big(y(s)\big)\,ds\right)^T\right)^T N_1 \begin{pmatrix} y(t) \\ \bar{h}(y(t)) \\ \int_{t-\tau}^{t} \bar{K}(t-s)\bar{h}(y(s))\,ds \end{pmatrix} \\ &+ \left(y^T(t) \quad \bar{l}^T\big(y(t)\big) \quad \left(\int_{t-\tau}^{t} \bar{K}(t-s)\bar{l}\big(y(s)\big)\,ds\right)^T\right)^T N_2 \begin{pmatrix} y(t) \\ \bar{l}(y(t)) \\ \int_{t-\tau}^{t} \bar{K}(t-s)\bar{l}(y(s))\,ds \end{pmatrix}. \end{aligned} \tag{45}$$

The remaining proof is similar to the proof of Theorem 1, we omit it. This completes the proof. □

Moreover, in order to simplify the conditions in (43), we have the following theorem:

Theorem 4. *Under assumption* (A_1)*, the equilibrium point of model* (28) *is globally asymptotically stable if there are positive definite diagonal matrices* $H = \mathrm{diag}(H_1, H_2, \ldots, H_n) \in \mathbb{R}^{n\times n}$*,* $\bar{J} = \mathrm{diag}(\bar{J}_1, \bar{J}_2, \ldots, \bar{J}_{Nn}) \in \mathbb{R}^{Nn\times Nn}$*, and positive definite matrices* $P = (p_{ij})_{n\times n}$*,* $Q = (q_{ij})_{n\times n}$*,* $\bar{R} = (\bar{r}_{ij})_{Nn\times Nn}$*, such that*

$$N_1' = \begin{pmatrix} -PC & PA + FH & PB \\ AP + HF & \tau^2 K^T(0) Q K(0) - 2H & 0 \\ B^T P & 0 & -Q \end{pmatrix} < 0, \tag{46}$$

$$N_2 = \begin{pmatrix} -\bar{P}\bar{C} & \bar{P}\bar{\Gamma} + \bar{G}\bar{J} & \bar{P}\bar{\Lambda} \\ \bar{\Gamma}^T\bar{P} + \bar{J}\bar{G} & \tau^2 \bar{K}^T(0)\bar{R}\bar{K}(0) - 2\bar{J} & 0 \\ \bar{\Lambda}^T\bar{P} & 0 & -\bar{R} \end{pmatrix} < 0, \tag{47}$$

where

$$F = \mathrm{diag}(F_1, F_2, \ldots, F_n) \in \mathbb{R}^{n\times n}, \qquad \bar{F} = E_N \otimes F,$$
$$G = \mathrm{diag}(G_1, G_2, \ldots, G_n) \in \mathbb{R}^{n\times n}, \qquad \bar{G} = E_N \otimes G.$$

Proof. Let $\bar{P} = E_N \otimes P$, $\bar{H} = E_N \otimes H$ and $\bar{Q} = E_N \otimes Q$ in Theorem 3, then we can easily get

$$\begin{aligned}&\left(y^T(t) \quad \bar{h}^T\big(y(t)Q\big) \quad \left(\int_{t-\tau}^{t} \bar{K}(t-s)\bar{h}\big(y(s)\big)\,ds\right)^T\right)^T N_1 \begin{pmatrix} y(t) \\ \bar{h}(y(t)) \\ \int_{t-\tau}^{t} \bar{K}(t-s)\bar{h}(y(s))\,ds \end{pmatrix} \\ &\quad = \sum_{i=1}^{i=N} \left(y_i^T(t) \quad h^T\big(y_i(t)\big) \quad \left(\int_{t-\tau}^{t} K(t-s)h\big(y_i(s)\big)\,ds\right)^T\right)^T N_1' \begin{pmatrix} y_i(t) \\ h(y_i(t)) \\ \int_{t-\tau}^{t} K(t-s)h(y_i(s))\,ds \end{pmatrix}. \end{aligned}$$

The remaining proof is straightforward and hence omitted. □

Remark 1. Since N_1' in (46) and N_1 in (43) are $3n \times 3n$ and $3Nn \times 3Nn$ matrices, respectively, one can see that Theorem 4 may be more useful and simple as the nodes' number N of the network is large.

Remark 2. For semantic grid or virtual organizations, there are very few models that can be used to discuss their reputation computation. Since a node in the new complex network is a fundamental unit with detailed contents about an entity in the virtual organizations, we can use it to study the reputation computation for virtual organizations. It is a new method to solve this problem based on our new network model, which can well show the dynamics for reputation degrees in virtual organizations.

Remark 3. Stability of complex network model implies that the reputation degrees of entities converge to some fixed constants. Also, as is known to all that there are some other dynamical behaviors in the complex network model such as bifurcation, chaos which indicate that the reputation degrees of entities change irregularly. However synchronization means that we may consider some entities as alliances. The reputation degree of the same alliances may change but they change in the same way.

4. A numerical example

In this section, we give a simulation example to verify the results obtained in this Letter.

Example. Consider the following complex network:

$$\dot{x}_i(t) = -Cx_i(t) + Af\big(x_i(t)\big) + B\int_{t-\tau}^{t} K(t-s)f\big(x_i(s)\big)\,ds + I_i + \sum_{j=1}^{N} d_{ij}\left[\Gamma g\big(x_j(t)\big) + \Lambda\int_{t-\tau}^{t} K(t-s)g\big(x_j(s)\big)\,ds\right],$$
$$i = 1, 2, \ldots, N, \tag{48}$$

where

$$C = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad A = \begin{pmatrix} 0.2 & -0.1 \\ 0.3 & 0.2 \end{pmatrix}, \quad B = \begin{pmatrix} 0.2 & 0.4 \\ 0.2 & -0.1 \end{pmatrix}, \quad I_1 = \begin{pmatrix} 0.1 \\ 0.2 \end{pmatrix}, \quad I_2 = \begin{pmatrix} 0.7 \\ 0.6 \end{pmatrix}, \quad I_3 = \begin{pmatrix} 0.4 \\ 0.3 \end{pmatrix},$$
$$f(x_i) = \begin{pmatrix} \tanh(x_{i1}) \\ \tanh(x_{i2}) \end{pmatrix}, \quad g(x_j) = \begin{pmatrix} \tanh(x_{j1}) \\ \tanh(x_{j2}) \end{pmatrix} \quad (i, j = 1, 2, 3), \quad \tau = 1,$$
$$\Gamma = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad \Lambda = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad K(s) = \begin{pmatrix} e^{-s} & 0 \\ 0 & e^{-s} \end{pmatrix}, \quad D = \begin{pmatrix} -0.5 & 0.5 & 0 \\ 0.2 & -0.6 & 0.4 \\ 0 & 0.3 & -0.3 \end{pmatrix}.$$

It is obvious to see that $F = G = \left(\begin{smallmatrix} 1 & 0 \\ 0 & 1 \end{smallmatrix}\right)$. Using LMI toolbox in Matlab, from Theorem 1, we obtain

$$\bar{P} = \begin{pmatrix} 315.1818 & 0.7146 & 57.1610 & 4.3380 & -9.8276 & -2.5261 \\ 0.7146 & 303.8076 & 3.2680 & 52.9551 & -2.4333 & -9.3308 \\ 57.1610 & 3.2680 & 401.8530 & 16.5816 & 59.9312 & 6.8004 \\ 4.3380 & 52.9551 & 16.5816 & 365.7212 & 7.2141 & 54.2814 \\ -9.8276 & -2.4333 & 59.9312 & 7.2141 & 450.9577 & 24.1372 \\ -2.5261 & -9.3308 & 6.8004 & 54.2814 & 24.1372 & 419.0998 \end{pmatrix},$$

$$\bar{Q} = \begin{pmatrix} 131.6387 & -8.2155 & 17.0714 & 1.4625 & -12.9198 & 0.4488 \\ -8.2155 & 173.0465 & 1.4410 & 15.0339 & 0.4397 & -9.4750 \\ 17.0714 & 1.4410 & 145.3723 & -0.9967 & 11.5466 & 3.1216 \\ 1.4625 & 15.0339 & -0.9967 & 194.7709 & 2.8133 & 11.8521 \\ -12.9198 & 0.4397 & 11.5466 & 2.8133 & 191.1770 & -2.5945 \\ 0.4488 & -9.4750 & 3.1216 & 11.8521 & -2.5945 & 234.9790 \end{pmatrix},$$

$$\bar{R} = \begin{pmatrix} 280.7083 & 2.3349 & -102.5644 & -21.4834 & -4.1913 & -2.8780 \\ 2.3349 & 273.4791 & -23.0698 & -85.2130 & -2.2688 & -3.3209 \\ -102.5644 & -23.0698 & 427.9622 & 17.6665 & -128.6232 & -27.1065 \\ -21.4834 & -85.2130 & 17.6665 & 392.6001 & -26.9793 & -102.3020 \\ -4.1913 & -2.2688 & -128.6232 & -26.9793 & 313.6618 & 2.7203 \\ -2.8780 & -3.3209 & -27.1065 & -102.3020 & 2.7203 & 301.0954 \end{pmatrix},$$

$$\bar{H} = \begin{pmatrix} 236.8081 & 0 & 0 & 0 & 0 & 0 \\ 0 & 225.7796 & 0 & 0 & 0 & 0 \\ 0 & 0 & 274.2453 & 0 & 0 & 0 \\ 0 & 0 & 0 & 249.1510 & 0 & 0 \\ 0 & 0 & 0 & 0 & 311.1474 & 0 \\ 0 & 0 & 0 & 0 & 0 & 295.2271 \end{pmatrix},$$

$$\bar{J} = \begin{pmatrix} 230.4325 & 0 & 0 & 0 & 0 & 0 \\ 0 & 232.4224 & 0 & 0 & 0 & 0 \\ 0 & 0 & 358.1391 & 0 & 0 & 0 \\ 0 & 0 & 0 & 338.1173 & 0 & 0 \\ 0 & 0 & 0 & 0 & 325.7547 & 0 \\ 0 & 0 & 0 & 0 & 0 & 310.4898 \end{pmatrix}.$$

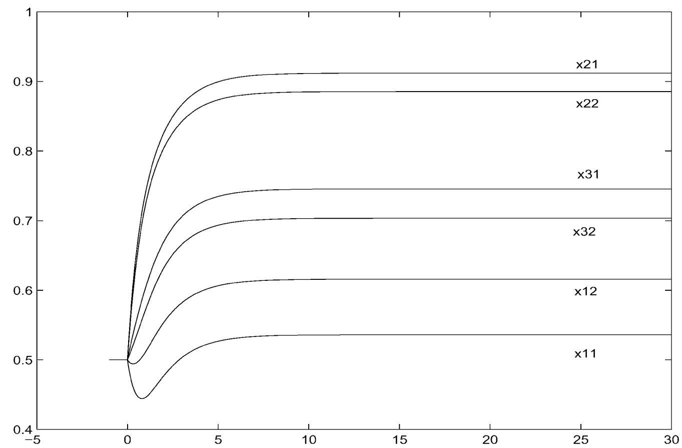

Fig. 1. Trajectories of nodes in complex network.

By Theorem 1, we conclude the complex network model (48) is globally asymptotically stable. The simulation result is given in Fig. 1, which shows the correctness of the results given in this Letter.

5. Conclusions

In recent years, the semantic grid and virtual organizations have become a hot topics, but the corresponding results especially the dynamical models and convergence dynamics for their reputation computation of virtual organizations or semantic gird are still lacking. In this Letter, a new complex network model has been built for computing or formulating the reputation degrees for virtual organizations. Some simple convergence dynamics have been discussed for the reputation degrees of entities in virtual organizations, and the stability have showed that the reputation degrees of entities can tend to some fixed constants as time evolves. As a start on this new model, here we have only presented some simple analysis such as stability, further research on this new model will be addressed in the near future.

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