# Implementation of Control Measure in the Crisis Using Social Networks

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***Abstract* — The social networks play an important role in information dynamics. The social media introduces the complex network theory in the form of social networks. The important information can be retrieved in the form of specific keywords. These specific keywords give the informatics digraph from which the future impact of information can be predicted. The role of social network through the social media plays an important role in various domains like: social security, terrorist attack, geographical crisis, infectious virus epidemic and community crisis. This paper presents the social media based digraph modeling carrying specific keywords used to detect the impact of information on social connected community through: Facebook, Twitter, Flicker, and YouTube. These informatics digraphs are constructed through the condensation of links with equivalent weights, connected to the nodes with high out degrees. The different communities are identified from the state transition matrix of the extracted digraph with same eigenvalues. By predicting the futuristic impact of these distinct communities, one can apply the control measures on them.**

***Keywords - component; social network visualization; graphs and networks; directed digraphs; transition matrix; Jordan blocks***

## I. INTRODUCTION

The social media has become a best medium of interaction between the people [1], [2], [3]. A social network is created when discussion is viral on social media [4]. The social network is playing an important role, as communities' discussion and opinions are important keys for future scenario prediction. Now a day, the utility of internet is maximum for the overall effective analysis related to: market prediction, virus epidemics, opinion polls before the elections, distinct solution of common problem discussed on an internet forum [5]. When a discussion is viral on internet, the participants get clustered due to same acuities [6]. A problem can become solution centric when number of participants increases. The maximum number of conversations on a social media becomes the weighted links of extracted social networks [7]. Modeling the world around us in the form of social network on a common issue, gives the better solution or prediction for a problem discussed over internet [8], [9], [10], [11], [12]. The social networks established through the social media can also be mapped in the defined topologies like:

1) Disconnected cluster of peoples where groups of peoples are not all connected.
2) Tightly connected groups.
3) A nexus pattern, where individual share the multiple contexts with ego.
4) The butterfly pattern where the different groups are connected by one person.
5) The star pattern where all the clusters are connected by one person.
6) The ring pattern

The influencers inside the social network are on the bases of:

1) Popularity of individual with in the community
2) Number of supporting individuals to a person
3) Group strength
4) Number of interactions along a single person
5) The quality of content discussed in the social media
6) Common interest with other community members

In today's world, the number of people participating in social network sites, using their smart gadgets, are increasing exponentially with time [13], [14], [15]. The future technology will also include the IP integrated devices in which the participants will be Human and machines. The properties listed in Table-I intuits the prediction of topic intensity discussed in the social network [16].

TABLE I. SOCIAL NETWORK PROPERTIES

| Property | Examination of Network Property |
|---|---|
| User activity in the network | Duration of activation |
| Diffused information contents | Should be of high quality |
| Expertise | The knowledgeable person who can give the solution/advise |
| Influence | Degree of information diffusion |
| Network structure | No two links have the same weight |
| Novelty | New things/ideas proposed |
| Trust | Maximum user with same opinion |

Many researchers have applied different schemas for social network analysis based on human emotional dimensions as well as complex network properties like:

1) Spirit of conversation
2) Trust on influencer
3) Problem solutions
4) Administrator
5) Network flow
6) Shortest Path problem
7) Transport problem

An effort has been made in this paper to model the established social network as weighted signal digraph [17]. The information processing elements defined in this paper, are used to compute the signal flow graph. The communities involved in the connected network, are identified through the canonical form of social network. The degree of influence through each community, involved in the discussion, can predict the future impact of social network in the form of crisis. The proposed mathematical model is very useful for the transient analysis of social network [18], [19].

The rest of paper is organized as follows: Section II has discussed the preliminaries, basic definitions of social networks, and tools used to generate social network. The classification of different information processing elements is discussed in Section III. A weighted signal flow graph is extracted from the social network in Section IV. Section V gives the formation of canonical model of social network derived from weighted signal flow graph. Finally, the drawn conclusion and future scope are discussed in Section VI.

## II. PRELIMINARIES AND BACKGROUND

Table II gives the list of types of social media with different services

TABLE II. SOCIAL NETWORK PROPERTIES

| Properties | Type of Social Media | Examples |
|---|---|---|
| **Asynchronous Conversation** | Email lists, Usenet newsgroups, discussion forums, BBS, Email | MS Outlook, yahoo! Mail, AIM Mail, hotmail ,Gmail, listserv , yahoo! Answers, yahoo! Groups, Google, Slashdot |
| **Synchronous Conversations** | Audio and video conferencing, texting, instant messaging, chat | Window's live, ichat, Gizmo, Skype, chacha, AIM, Google Talk, MSN Messenger, yahoo! Messenger, IRc, UNIX Talk |
| **World Wide Web** | homepages, and government websites and documents, organizational, corporate | family history websites, ones' portfolio web page, Faculty member home page |
| **Collaborative Authoring** | Shared documents, Wiki | Etherpad, zoho, Google Docs, wetpaint, pbwiki, Wikia (lostpedia), Wikipedia, |
| **Blogs and Podcasts** | Multimedia blogs and podcasts, Microblogs and activity streams, Blogs | podcasts (iTunes, NPR), moblog (mobile blogging such as moblog.net), photo blogs (Fotolog, FAIlblog.org), Vlogs (video blogs such as Qik), Activity Streams, ,Buzz ,yammer ,Twitter ,WordPress ,Blogger, LiveJournal. |
| **Media sharing networks** | books, news, Bookmarks, Music, Photo and art, Video and TV | citeulike, libraryThing, Goodreads, StumbleUpon ,Reddit, Digg, Delicious, Garden Sonic, imeem, Fm.last, deviantART, Picasso, Flickr, chatroulette ,Vimeo, netflix, hulu, youTube. |
| **Social Networking Services** | niche networks, Professional, Social and dating | Grou.ps ,Ravelry , ning(e.g.,classroom2.0), XInG ,Plaxo, linkedIn, Match, eharmony, Tagged ,BlackPlanet, MySpace, Facebook. |
| **Online Markets and Production** | Review sites, User generated products, Financial transaction | yelp, Angies'list, Amazon, ePinions, codeplex, Sourceforge, Topcoder, Threadless, Instructables, kiva, craigslist, Amazon, eBay. |
| **Idea Generation** | challenge sites, selection, Idea generation | Imaginatik ,IdeaScale ,chaordix ,Ideaconnection |
| **Mobile-Based Services** | games, annotation, location sharing | ScVnGR, letterboxing, Geocaching, MapMyRun ,loopt, Gowalla, Foursquare |
| **Online reviews** | User reviews about technology product or technical flaw | EDA ,Twitter |
| **Virtual Worlds** | Massively multiplayer games, Virtual reality worlds | Aion, lord of the Rings Online ,World of Warcraft , habbo, Webkinz , club Penguin, Second life |

### A. *Important Properties of Social Networks*

The following properties are very important for analysis of social networks:

i. Components:

Component distribution is very important property of social network graph. A connected component is a set of nodes and edges in the networks. A cyclic connected digraph is known as strong component of social network generated graph.

ii. Diameter:

Diameter of a graph is defined as the maximum distance between two nodes, with minimum numbers of hops.

iii. Degree centrality:

Degree centrality is total number of links connected to a vertex. In social networks, it measures the popularity of a person connected to many persons in society. Degree centrality finds the most influence node with in the graph and most influence person with in the social networks.

iv. Betweenness centrality:

It is the centrality measure of a node with in the graph and in social networks, it is the centrality measure of a person with in the social networks. It qualifies the number of times a person act as a bridge during the interaction of two persons in social network.

v. Closeness centrality:

A low closeness centrality in a social network means a person is just one hop away from other persons in the social network. Closeness can be measured as a reciprocal of farness of a node. Whereas the farness of a node defined as the sum of its distances from all other nodes.

vi. Eigenvector Centrality:

It is the measure of the centrality of a person in a social network, who is connected to other persons, who themselves with a high degree of centrality.

### B. *Tools for Social Network Analysis*

There are many tools used for the mathematical and statistical analysis of social networks. These tools can directly import the social media streams and export the contents as social networks matrices. The most popular tools are:

i. NODE XL:

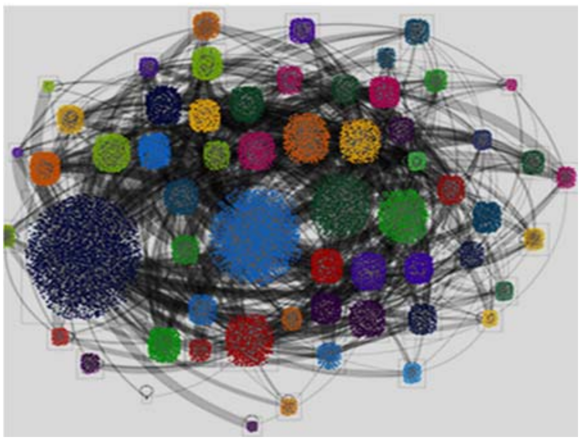

Figure 1. Diffirent groups of people connected through a social network created by NODE XL

NODE XL is an add-on templet with Microsoft Excel. It provides the easy access social media network data stream, like: YouTube, Facebook, Twitter and, Flicker. The generated data set in an excel sheet can be used to calculate the advanced networks matrices as well as statistical analysis. A social network created by NODE XL for different communities is shown in Figure 1.

ii. Gephi:

Gephi is free open source software can be used for exploration and visualization of social networks. Gephi can be used for following applications:

1. Exploratory data analysis:

Diffused information oriented analysis in real time.

2. People connection analysis:

Type of bondage between the peoples in social network. It reveals the information flow as well as human nature involved in the social network.

3. Social Network Analysis:

Calculate the important network matrices extracted from the various social media streams.

4. Biological Network analysis:

Used to plot the pattern for extracted biological data.

A social network created by Gephi for different communities is shown in Figure 2.

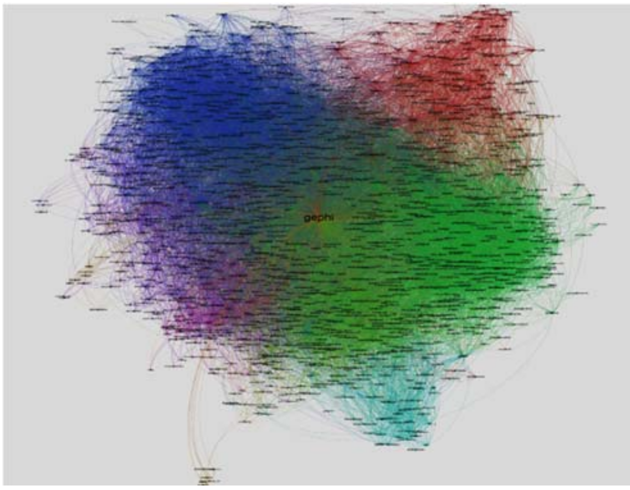

Figure 2. Diffirent groups of people connected through a social network created by Gephi

## III. INFORMATION PROCESSING ELEMENTS IN SOCIAL NETWORKS

The processing elements in the social networks, are the basic information elements created by individuals and group of persons in connected network. There are four types of information processing elements used to construct information signal flow graph. The formation of these elements depends upon the type of information diffused in social network. These processing elements are:

### A. *Information Restriction Element*

This element does not allow the full information to move from one person to another person connected through the social network. This element act as obstruction to the full

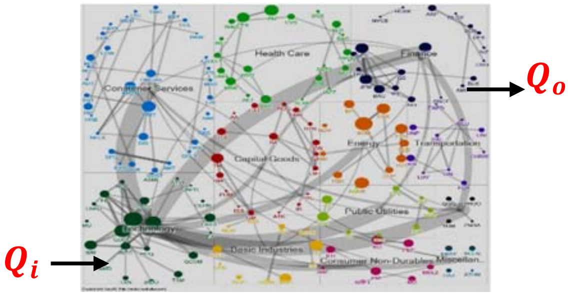


Figure 3. Information Restriction Element

Information flow in the fully connected social network. The transfer function of information restriction element is given by:

$$G(S) = \frac{D}{Q_i} = R \tag{1}$$

where: D is the maximum diameter of social network, R is the restriction to information flow, $Q_i$ is input information flow and $Q_o$ is received information.

### B. Information Flaming Element

Flaming elements amplify the diffused information and make it more egocentric. The contents at receiving end are more amplified and flamed.

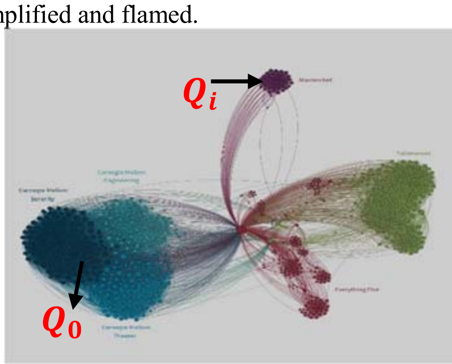


Figure 4. Information Flaming Element

The transfer function of information flaming element is given by:

$$G(S) = \frac{Q_0}{Q_i} = A \tag{2}$$

where: A is the flaming factor to information flow, $Q_i$ is input information flow and $Q_o$ is received amplified information.

### C. Information Harvesting Element

The diffused information in a community will never goes out of it. The characteristics of information harvesting element depends on the number of persons in that community. Harvesting of information may prevent the flaming in connected communities in social networks. The transfer function of information flaming element is given by:

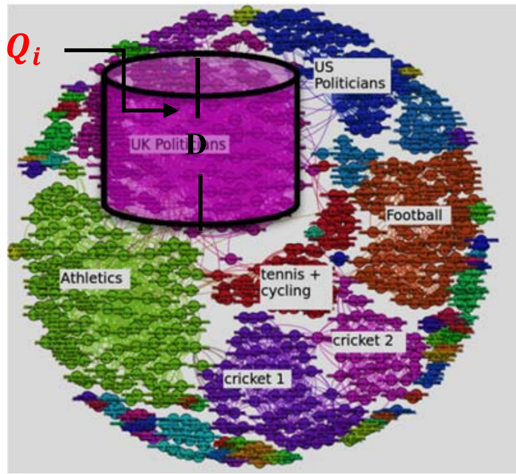


Figure 5. Information Harvesting Element

$$G(S) = \frac{D}{Q_i} = \frac{1}{CS} \tag{3}$$

where: D is the maximum diameter of specific community in social network, and $Q_i$ is input information flow.

### D. Information Delay Element

This element in the social networks, transfer the information from one community to another community with a time delay. If D is the maximum diameter of specific community, which is source of information, in social network; R is the restriction to information flow; $Q_i$ is input information flow and $Q_o$ is delivered information with a delay, to another community. The transfer function of information delay element is given by:

$$G(S) = \frac{D}{Q_i} = \frac{R}{(RCS+1)} = \frac{R}{(\tau S+1)} \tag{4}$$

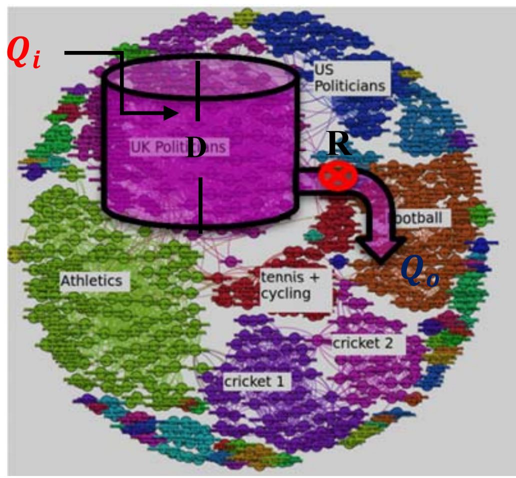


Figure 6. Information Delay Element

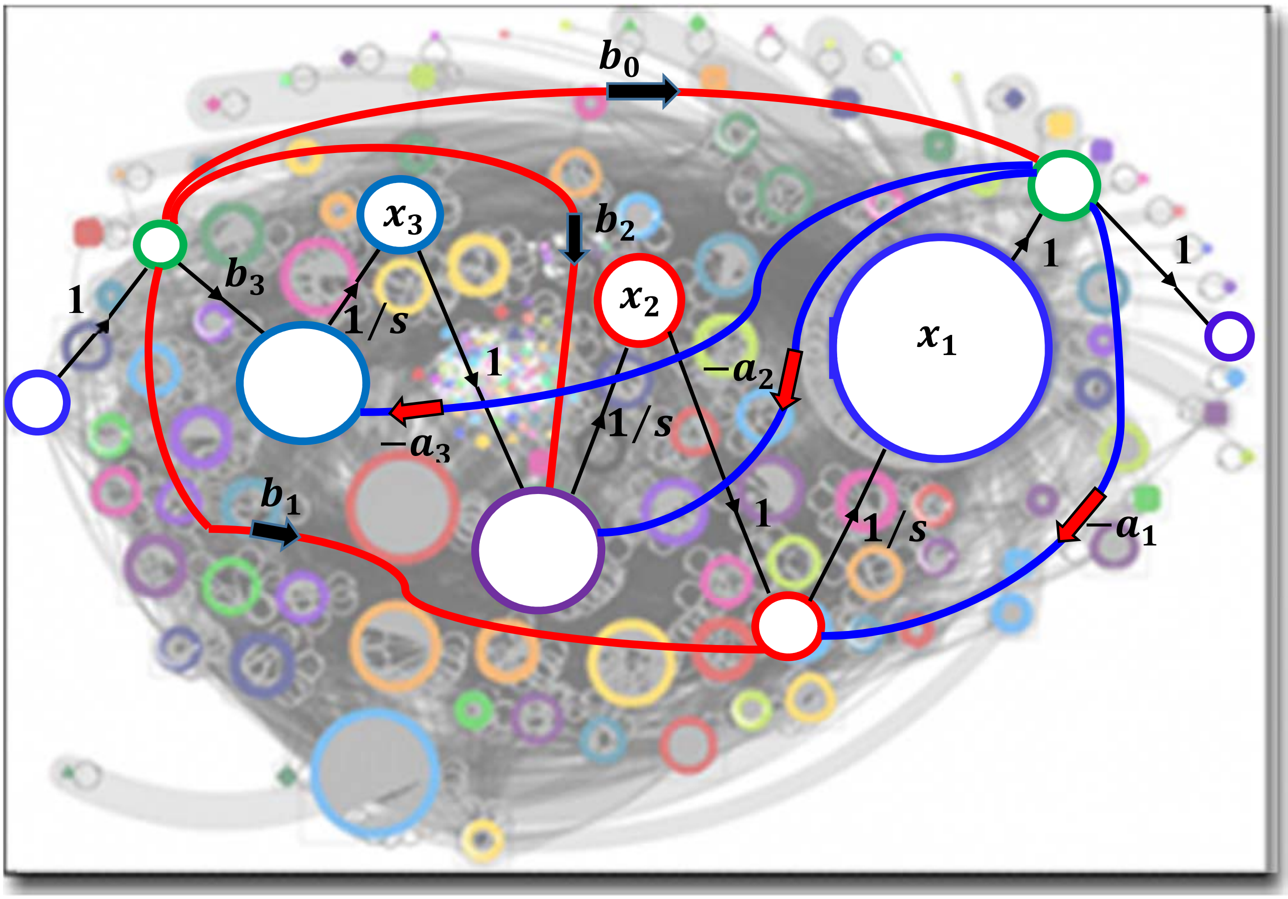


Figure 7. Established Information Flow Graph from Social Networks

## IV. WEIGHTED SIGNAL FLOW GRAPH EXTRACTED FROM SOCIAL NETWORK

The processing elements in a social network are identified with the measured entropy. Input of a defused information with these identified information processing elements, forms an information flow graph as shown in the Figure 7. The derived transfer function of extracted information flow graph is:

$$T(s) = \frac{1}{\Delta}\sum_k P_k \Delta_k \tag{5}$$

Where $P_k$ is the forward path gain of k[th] path; $\Delta$ = 1- (sum of loop gains of all individual loops) + (sum of gain product of all possible combination of two non-touching loops) - (sum of gain product of all possible combination of three non-touching loops) + … so on. $\Delta_k$ is the value of $\Delta$ calculated from the part of graph which is no touching k[th] forward path.
From figure 7, three individual loops are:
$-a_1/s$ , $-a_2/s^2$, and $-a_3/s^3$ and four forward path are: $b_0, b_1/s, b_2/s^2$, and $b_3/s^3$. Using Equation (5), the transfer function of extracted information flow graph is:

$$T(s) = \frac{b_0 + b_1/s + b_2/s^2 + b_3/s^3}{1-(-a_1/s - a_2/s^2 - a_3/s^3)} \tag{6}$$

Equation (6) gives third order transfer function.

$$T(s) = \frac{b_0 s^3 + b_1 s^2 + b_2 s + b_3}{s^3 + a_1 s^2 + a_2 s + a_3} \tag{7}$$

Equation (7) gives the dynamics of information propagation in a social network. The impact of diffused information can be studied on last connected community as well as intermediate communities, acting as the bridge for information flow. The response of each community towards diffused information can be studied with state space model [20]. the Equation 7 of order $n$, can be written in the form of partial fraction as:

$$T(s) = b_0 + \sum_{i=1}^{n} \frac{c_i}{s-\lambda_i} \tag{8}$$

where $c_i$ are the residue of the poles at $s = \lambda_i$.
The Jordan canonical form of this information digraph is:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \vdots \\ \dot{x}_n \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 & 0 & \cdots & 0 \\ 0 & \lambda_2 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & \lambda_n \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} u \tag{9}$$

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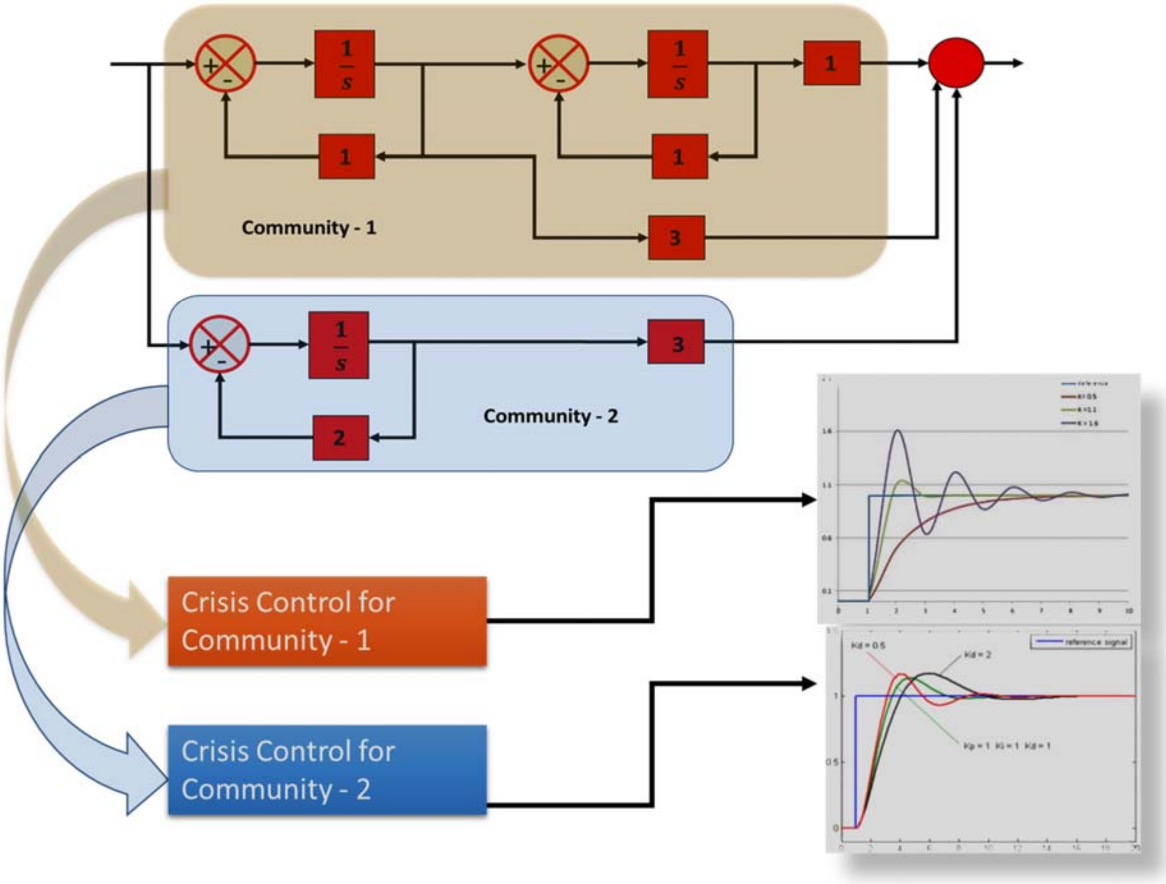


Figure 8. Jordan Canonical form of communities

$$y = [c_1 \quad c_2 \quad \cdots \quad c_n]\begin{bmatrix}x_1\\x_2\\ \vdots \\x_n\end{bmatrix} + b_0\,u \qquad (10)$$

## V. JORDAN CANONICAL FORM INFORMATION DIGRAPH

The Jordan canonical formation of communities involved in social network information digraph, is very useful to identify the types of communities involved in the social network to carry the information from one person to other person. For example, if the transfer function derived from the established information flow graph is:

$$T(s) = \frac{2s^2 + 6s + 7}{(s+1)^2(s+2)}$$

Using Equation (8):

$$T(s) = \frac{-1}{(s+1)} + \frac{3}{(s+1)^2} + \frac{3}{(s+2)}$$

Using Equation (9), the Jordon canonical form of this community digraph is:

**Community-1** **Community-2**

$$\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\\ \dot{x}_3\end{bmatrix} = \begin{bmatrix}-1 & 1 & 0\\ 0 & -1 & 0\\ 0 & 0 & -2\end{bmatrix}\begin{bmatrix}x_1\\x_2\\x_3\end{bmatrix} + \begin{bmatrix}0\\1\\1\end{bmatrix}[u]$$

**Jordan Block**

$$y = [-1 \quad 3 \quad 3]\begin{bmatrix}x_1\\x_2\\x_3\end{bmatrix}$$

The communities in the Jordon blocks are not decoupled due to similar user in them (because of repeated root at $s = -1$) as shown in Figure 8. This is the best way to identify the similar communities in a connected social network. The control action applied to the community is depends upon the information dynamics of that community. Algorithm 1 gives the, control measures with various possibilities compatible with several situations across the different communities connected in the social network.

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**Algorithm 1: Control algorithm for crisis in a community connected in social network.**

1. For community identification, break social network in the form of Jordan canonical model.
2. Check the possibility of crisis across each community:
   $I_{Diff}$ ← Information Diffusion Time
   $F_{Peak}$ ← Flaming Peak
   $F_{Set}$ ← Flaming Settling Time
   $Com_{Un}$ ← Uncorrected Community
   $Com_{Sta}$ ← Stable Community
3. Apply the control law:
   **Com** ← Identified Community
   **CL** ← Control Law
   $\boldsymbol{If}(\text{Com} == I_{Diff} \uparrow \&\&F_{Peak} \uparrow \&\&Com_{Un} \uparrow \&\&Com_{Sta} \downarrow)$
   $CL == K_p$ \\\\ Proportional Control
   ***Else***
   $\boldsymbol{If}(\text{Com} == I_{Diff} \uparrow \&\&F_{Peak} \downarrow \&\&\boldsymbol{F_{Set}} \downarrow \&\&Com_{Un} \uparrow \&\&Com_{Sta} \uparrow)$
   $CL == K_p + \frac{K_i}{s}$ \\\\ Proportional Integral Control
   $\boldsymbol{Else}(\text{Com} == I_{Diff} \uparrow \&\&F_{Peak} \uparrow \&\&\boldsymbol{F_{Set}} \uparrow \&\&Com_{Un} \uparrow \&\&Com_{Sta} \downarrow)$
   $CL == K_p + \frac{K_i}{s} + K_d\, s$ \\\\ Proportional Integral and Derivative Control

The control system controls the situations which may lead to a crisis with in a community.

## VI. CONCLUSION

It is very important to identify the catalysis of flaming in an egocentric community, to prevent the crisis occurrence. The mathematical model discussed in this paper is very suitable for community identification. Once the community is identified, an individual control measure can be applied to each community. Cyber enabled devices like smart phones, play a very important role in social networks. The IDs and location of such devices, which are being used in egocentric conversations, can be identified with the persons who are using them. This work helps to identify the awkward community and, scroll a particular group of people who may cause a crisis in an identified community. The proposed work is suitable with all social networking tools, discussed in this paper.

## REFERENCES

[1] U. Brandes, J. Pfeffer, and I. Mergel, Studying Social Networks: AGuide to Empirical Research. Frankfurt, Germany: CampusVerlag Gmbh, 2012.

[2] M.E.J. Newman, D.J. Watts, and S.H. Strogatz, ''Random Graph Models of Social Networks,'' Proc. Nat. Acad. Sci. USA, vol. 99, suppl.1, pp. 2566-2572, February, 2012.

[3] Y. Jiang, J. Hu, and D. Lin, ''Decision Making of Networked Multiagent Systems for Interaction Structures,'' IEEE Trans. Syst., Man, Cybern. A, Syst. Humans, vol. 41, no. 6, pp. 1107-1121, Nov. 2011.

[4] G. Caldarelli, Scale-Free Networks: Complex Webs in Nature and Technology. Oxford, U.K.: OUP Catalogue, 2011.

[5] J. Scott, Social Network Analysis. Thousand Oaks, CA, USA: SAGE Publications Limited, 2012.

[6] M. Girvan and M.E.J. Newman, ''Community Structure in Social and Biological Networks,'' Proc. Nat. Acad. Sci. USA, vol. 99,no. 12, pp. 7821-7826, July 2002.

[7] Y. Zhao, E. Levina, and J. Zhu, ''Community Extraction for Social Networks,'' Proc. Nat. Acad. Sci. USA, vol. 108, no. 8, pp. 7321-7326, May 2011.

[8] O. Yag˘ an and V. Gligor, ''Analysis of Complex Contagions in Random Multiplex Networks,'' Phys. Rev. E, vol. 86, no. 3, p. 036103, Sept. 2012.

[9] C.-T. Li, S.-D. Lin, and M.-K. Shan, ''Influence Propagation and Maximization for Heterogeneous Social Networks,'' in Proc. 21st WWW Companion, Lyon, France, Apr. 16-20, 2012, pp. 559-560.

[10] J. Go´mez-Garden˜ es, I. Reinares, A. Arenas, and L.M. Florı´a, ''Evolution of Cooperation in Multiplex Networks,'' Sci. Rep., vol. 2, p. 620, Aug. 2012.

[11] Y. Jiang, ''Concurrent Collective Strategy Diffusion of Multiagents: The Spatial Model and Case Study,'' IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol. 39, no. 4, pp. 448-458, July 2009.

[12] M. Gomez-Rodriguez, J. Leskovec, and A. Krause, ''Inferring Networks of Diffusion and Influence,'' ACM Trans. Knowl. Discovery Data, vol. 5, no. 4, p. 21, Feb. 2012.

[13] J. Duch, J.S. Waitzman, and L.A.N. Amaral, ''Quantifying the Performance of Individual Players in a Team Activity,'' PloS One, vol. 5, no. 6, p. e10937, June 2010.

[14] M. Youssef and C. Scoglio, "Mitigation of epidemics in contact networks through optimal contact adaptation," Math. Biosci. Eng., vol. 10, no. 4, pp. 1227–1251, 2013..

[15] C.D. Brummitt, K.M. Lee, and K.I. Goh, ''Multiplexity-Facilitated Cascades in Networks,'' Phys. Rev. E, vol. 85, no. 4, p. 045102(R), Apr. 2012.

[16] S.V. Buldyrev, R. Parshani, G. Paul, H.E. Stanley, and S. Havlin, ''Catastrophic Cascade of Failures in Interdependent Networks,'' Nature, vol. 464, no. 7291, pp. 1025-1028, Apr. 2010.

[17] Y. Jiang and J. C. Jiang, "Diffusion in social networks: A multiagent perspective," IEEE Trans. Syst., Man, Cybern., Syst., vol. 45, no. 2, pp. 198–213, Feb. 2015.

[18] J. Wang and I. C. Paschalidis, "Statistical traffic anomaly detection in time-varying communication networks," IEEE Transactions on Control of Network Systems, vol. 2, no. 2, pp. 100–111, 2015.

[19] J. Bollen, B. Goncalves, G. Ruan, and H. Mao, ''Happiness is Assortative in Online Social Networks,'' Artif. Life, vol. 17, no. 3, pp. 237-251, Sept. 2011.

[20] Xiaoping Wang, Yunliang Zhao and Yuanqing Liao, "Dynamic performance analysis of PID controller with one memristor," Information Science and Technology (ICIST), 2011 International Conference on, Nanjing, 2011, pp. 1234-1237.