A Firm-Growing Model and the Study of Communication Patterns' Effect on the Structure of Firm's Social Network

Liang Chen[1], Haigang Li[1], Zhong Chen[1], Li Li[1,3], and Da-Ren He[2]

[1] Antai College of Economics and Management, Shanghai Jiaotong University, Shanghai, 200052, China
sanlychen@126.com
[2] College of Physics Science and Technology, Yangzhou University, Yangzhou, 225002, China
[3] Education College, Shanghai Normal University, Shanghai, 200234, China

Abstract. In this article, we propose a firm-growing model, and then collect empirical data to test model validity. The simulation results agree well with the empirical data. We next explore the effect of communication patterns on the growth and structure of firm's social network and find that the extents to which employees reluctantly interact within or across departments significantly influence the structure of firm's social network.

Keywords: firm-growing model, communication pattern, firm's social network structure.

1 Introduction

It is generally recognized that knowledge and the capability to create, learn and transfer knowledge is the source of firms' sustainable competitive advantage [1][2]. And the theory of social capital advocates that the structure of firms' social network, e.g., density, diversity and range, have significant effects on individual and organizational knowledge creation and transfer, as well as the performance [3][4]. In order to identify what fators could influence the evolution of firm's social network and consequently the structure of social network, some researchers obtain the snapshot of social network by using the traditional social research method, e.g., survey, case study and experiment[5]. However the cross-sectional data, which is observed at a single point in time, is not sufficiently rich enough to represent the dynamic subject, resulting in the failure to prove the cause-effect relationship between fators and structure of social networks.

The study of complex networks has recently attracted attentions across disciplines and also experienced a fast development. The application of complex network theory in the area of human society has also proved valuable. With progress in information technology, some researchers have investigated the structure of collaboration networks and social networks of interpersonal interactions maintained over the Internet. Some examples of such networks are scientist collaboration networks [6], e-mail networks [7], blog networks [8], and web-based

J. Zhou (Ed.): Complex 2009, Part II, LNICST 5, pp. 1374–1386, 2009.
© ICST Institute for Computer Sciences, Social Informatics and Telecommunications Engineering 2009

social networks of artificial communities [9]. Furthermore, Guimera [10] explore the effect of team assembly mechanism on the structure of collaboration network structure and team performance. So this article also employs the complex network theory in exploring the growth of firm's social networks in order to identify the factors that significantly influence the structure of those networks.

There are definitely physical and invisible boundaries among employees, e.g. physical distance, hierarchical boundaries and organization silos, and it is these boundaries that divide employees into groups [11][12]. These boundaries impede the communication across groups, therefore the mechanisms of communication within groups are different from those across groups. Moreover, there are two major patterns of communication influencing the formation and development of relationships between employees: (1) formal or compulsory interactions, e.g., the interactions formed in regular meeting of groups, between team members assigned to a single task, via direct reporting relationship between the subordinate and superior; (2)informal ones, e.g., chance encounters at:lunch, the water cooler, the copier, waiting for elevator, or around the coffee machine, strangers gather because of homophile or shared interest. In order to apply these features in an understanding of the evolution of firm's social networks, we propose, in this article, a firm-growing model in which the communications within the single group are different from those across the group boundaries in section 2. In section 3, we collect the empirical data and these data are compared with the simulation results in section 4. In section 5, we extensively explore how the organizational communication patterns affect the structure of social network, which offers insight into the formation and evolution of complex social networks and finally implications for management practice are suggested.

2 Model

In this section, we propose a firm-growing model in which the mechanisms of communication within the single group are different from those across the group boundaries, and both formal and informal communications apply. We exploit three generic features of organizational social networks: (i) a firm's social network is not static, but rather it grows through the continuous addition of new employees and through formal and informal interactions; (ii) employees are allocated to different functional groups (departments), which means that the actors in the network are not homogeneous; and (iii) concomitant with the heterogeneous characteristics of actors, the interactions between employees too are heterogeneous.

Using the language of a firm's growth to make the description more concrete, our growing network model is defined by the following rules:

2.1 Initialization

For simplicity, we assume that in a lattice of size $L \times L$, each cell i represents one position in a company and also has its coordinate (x_i, y_i) , which stands for individuals' physical location in the firm. So the *physical distance* between cell i and cell j follows Equation (1).

$$D_{ij}=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2} \tag{1}$$

And there are totally g functional groups or departments, for simplicity we use the term *group* instead of *department*. As we know, at the time when a new and small company is established, there are usually few employees in each department. So we set the number of employees in each group to be three, with one being the leader, the other two the subordinates. And then we connect every pair of the three employees of a single group.

2.2 Addition

At each time step, the firm recruits one employee as a result of the firm's expansion. This new employee i is randomly assigned to one of the current g functional groups. Let's assume Group m. Then in Group m, the probability to connect the new employee i to an old one j is

$$Pa_{ij} \propto \frac{e^{-D_{ij}}K(j)}{\sum_{j\in m} e^{-D_{ij}}K(j)} \tag{2}$$

where $K(j)$ denotes the neighbors or degrees of employee j .

2.3 Connecting within the Group

At each time step, there are two kinds of connections. One is between the leader and subordinates. Because of the unparalleled role the leader plays in the group, the members intend to communicate more with the leader than others, the probability for interaction between leader and subordinates follows the stochastic rule. The other connection is between subordinates. The probability, Pw_{ij}, of two given subordinates i and j interacting depends on the number of friends i and j each already has. We represent these factors by functions f . The possibility becomes

$$Pw_{ij}=f(i)f(j) \tag{3}$$

$$f(i)=\frac{1}{e^{\beta k(i)}+1} \tag{4}$$

where β is adjustable constant. It is apparently that each employee has limit time and energy to interact with definite friends, so those who have more friends are reluctant to acquaint with new friends; however those who have fewer friends tend to make new friends. Equation (3) reflects this effect, as β representing the extents to which an individual's apathy to communicate with others in the same group in Equation (4).

2.4 Connecting across Groups

At each time step, we launch certain number of projects that will need a random variable n groups ($n \leq g$) to participate, and these projects represent the formal and informal interactions across departments. For each selected group, one member will be chosen, and this is determined separately by two mechanisms: (i) the first one demands the most experienced employee to join in; (ii) the second would randomly choose any one. The first mechanism corresponds to the organization's formal interactions. The second one reflects the organization's informal interactions. For the reason that a single person has finite time and attention, he cannot participate in infinite projects. So we set a limit on the number of projects that each employee could participate. Some researches show that the tenure can be an indicator of employees' working experience [13], and then we use the tenure of each employee to represent his experience. In this paper, tenure is simply the number of time steps since the employee was recruited. For all the members of each project, each one is connected to every other. And we employ one parameter P to adjust the effects of both mechanisms. The possibility for the first mechanism to take effect is P , and the possibility for the second one is $(1 - P)$. The parameter P also implies the degrees to which employees' reluctance to interact across groups. When P is high, there are certain experienced employees who participate the inter-groups communication, while the rest are spared from the across-groups interactions. When P is low, more employees take an active part into the informal inter-groups communication.

Finally this simulation won't terminate until each cell has been filled with an employee. The result of the communications is the formation of relationships between employees, the aggregate of which is the firm's social network.

3 Empirical Data

In order to test the validity of firm-growing model, we collected the real firm's social network data by survey. In fact some management scholars and sociologists collect the data of firm's social network mainly by survey, while tracking email messages or repository logs are used too [14]. As a result of using survey, the process should be done carefully and then it costs much effort, which limits the amount of employees from whom we collected information. Despite this shortage, the method of survey helps to identify and capture the relationships between employees accurately, and some valuable findings have been made [15].

Two main qualities of relationships between employees are often discussed and studied by management scholars. The first is the tie strength, which is a concept ranging from weak ties at one extreme to strong ties at the other and characterizes the closeness and interaction frequency of a relationship between two actors [3][16]. The second is knowledge transfer [17]. Both types of relationships are relatively easy to identify and they are also the results of mutual communication between employees. So we collect the information on these two kinds of relationships between employees. If any pair of employees has either of these qualities, there is a link connecting them.

We developed the questionnaires by adopting several questions from the Ref. [18][19]. Then we conducted our survey in the R&D department of a Sino-German joint venture company (denoted here as Firm A), and in the R&D

department in a China state-owned company (denoted here as Firm B). Ninety-two engineers in Firm A and 94 engineers in Firm B completed the questionnaire, with the response rate being 100% and 93% respectively. Both R&D departments have the development of new products as their mission; automobile electronics for Firm A, and telecommunication equipment for Firm B. Both R&D departments have been divided into several groups or teams to develop different components. Since their establishment both departments have experienced rapid expansion - each originally had fewer than twenty members. The following comparison is made based on the information collected from the questionnaires.

4 Comparison between Empirical Data and Simulation Results

In this section, we analyzed the complex network features of the real network and also compare these properties with those of simulation results. Firstly, we introduce some parameters.

According to Ref. [20], network efficiency measures how efficiently it exchange information, and is defined as:

$$E=\frac{1}{N(N-1)}\sum_{i\neq j\in G}\frac{1}{d_{ij}} \tag{5}$$

Where d_{ij}indicates the path length of the shortest path between i and j , N is the amount of employees of the network, G is the set of vertices in the network.

The major difference between social network and other networks, including technological and biological network, is that social network shows assortative mixing [21]. Newman defined different assortativity coefficients according to the discrete and scalar characteristics of vertex respectively [22]. The discrete assortativity coefficient $r_{discrete}$ is defined as:

$$r_{discrete}=\frac{\sum_i e_{ij}-\sum_i a_i b_i}{1-\sum_i a_i b_i}=\frac{Tre-\|e^2\|}{1-\|e^2\|} \tag{6}$$

In Equation (6), e_{ij} is the fraction of connections that link an individual of Group i to the one of Group j. It satisfies the sum rules

$$\sum_{ij} e_{ij}=1 \quad \sum_j e_{ij}=a_i \quad \sum_i e_{ij}=b_j \tag{7}$$

a_i,b_i are the fractions of each group of end of a connection that is linked to employees of Group i.

And we also calculated the scalar assortativity coefficient r_{scalar}.

$$r_{scalar}=\frac{\sum_{jk} jk(e_{ik}-q_j q_k)}{\sigma_q^2} \tag{8}$$

$$q_k=\frac{(k+1)P_{k+1}}{z} \tag{9}$$

In Equation (8), $\sigma_q$is the standard deviation of the distribution q_k , and q_k is the excess degree of the vertex at the end of an edge which is distributed according

Table 1. Comparison between calculations of empirical data of Firm A, Firm B and those of the simulation results. For simulation 1, $\beta = 0.8$, $P = 0.96$; for simulation 2, $\beta = 0.8$, $P = 0.79$;

	N	$< k >$	C	C_{rand}	E	E_{rand}	r_{scalar}	$r_{discrete}$
Firm A	85	4.81	0.4430	0.0393	0.5092	0.5402	−0.2125	0.6163
Simulation 1	100	5.02	0.4786	0.0871	0.4013	0.5181	-0.1953	0.6163
Firm B	90	4.13	0.4221	0.0341	0.2873	0.3564	-0.2032	0.8621
Simulation 2	100	4.28	0.5465	0.0852	0.2038	0.4730	-0.2201	0.8663

to Equation (9),where P is the probability that a randomly chosen vertex will have degree k and $z = \sum_k kP_k$ is the mean degree in the network.

The basic network measurements of the Firm A's and Firm B's social network and the corresponding simulation results are listed in Table 4. Here we calculated the average degrees, clustering coefficient C, network efficiency E and assortativity coefficient based on the scalar and discrete vertex properties. We also presented the clustering coefficient C and network efficiency E of the random graph of Erdos and Renyi [23], in which edges are placed at random between a fixed set of vertices. The size and the possibility of the connection of the random graph are according to Firm A and Firm B respectively.

Several values deserve closer attention. First, from the values of C and E of both the empirical data and the random networks, we can conclude that both Firm A and Firm B social networks show the small-world effect. The results demonstrate that $E \leq E_{rand}$ but $C \gg C_{rand}$. Second, the values of r_{scalar} of both social networks are negative, which is inconsistent with the findings of Ref [24]. By contrast, the values of $r_{discrete}$ are positive, and relatively high. The comparison shows that the firm's social network is different from other social network.

4.1 Degree Distribution

Many empirical studies have shown that the degree distribution is mostly between a power law and an exponential decay [25][26]. Here we show in Fig. 1 the accumulative degree distribution of both real social network and the corresponding simulation results, which is a smooth function decreasing monotonously. As discussed in Refs. [27][28], we can describe the distribution with a shifted Poisson distribution. This shows that the number of relationships varies, but most of the values are located around the average.

4.2 Clustering

As mentioned in [21], clustering is one of the distinctive features of social networks. This is also the case of the firm's social networks, which show a large clustering coefficient, with $C = 0.443$ for Firm A and $C = 0.4221$ for Firm B. In Fig. 2, we plot the clustering coefficient as a function of the degree,$C(k)$, that is, the average clustering coefficient of vertices of degree k.

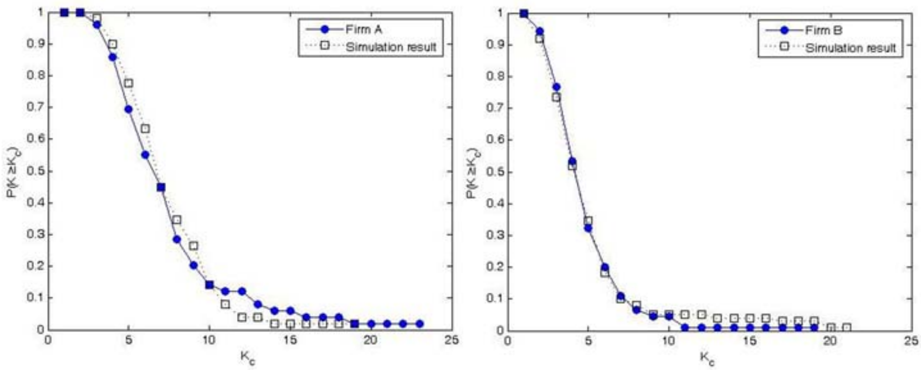

Fig. 1. Accumulative degree distribution of real networks and the corresponding simulation results with $N = 100$, $\beta = 0.8$, $P = 0.79$ and $N = 100$,$\beta = 0.8$, $P = 0.96$ respectively. The solid circles represent the empirical data. The empty squares represent the simulation result.

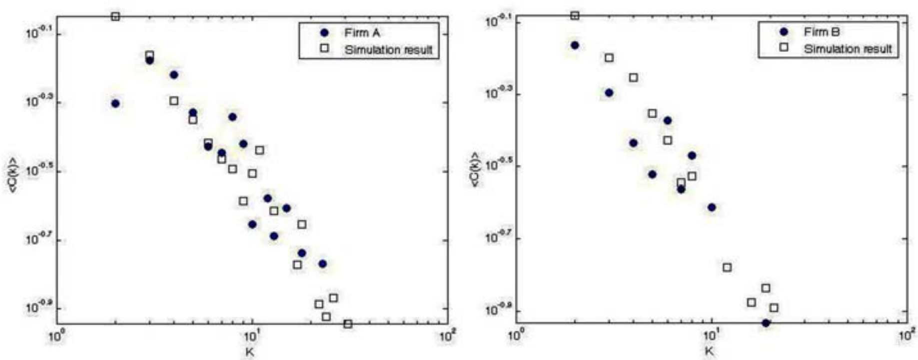

Fig. 2. The correlation between the local clustering coefficient and the node degree for the real social network, and their corresponding networks gained from the simulation with $N = 100$, $\beta = 0.8$, $P = 0.79$ and $N = 100$, $\beta = 0.8$, $P = 0.96$ respectively. The solid circles represent the data of the real network, and the empty squares represent the simulation result.

4.3 Betweenness

The betweenness of a vertex i is the number of geodesic paths between other vertices that run through it [29]. In Fig. 3, we also plot the relation of degree-Betweenness $B(k)$ for Firm A and Firm B.

Based on these comparisons of some measurements between the empirical data and simulation results in Table 1, Fig. 1, 2, 3, we may argue that the firm-growing model introduced in this article is capable of fitting the real firm's social network.

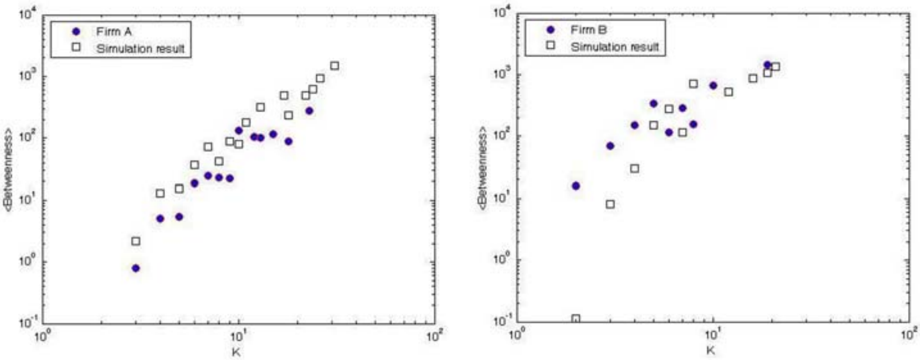

Fig. 3. The correlation between the local betweenness and the node degree for the Firm A's and Firm B's interpersonal relationships network, and the network gained from the simulation with $N = 100$, $\beta = 0.8$, $P = 0.79$ and $N = 100$, $\beta = 0.8$, $P = 0.96$ respectively. The solid circles represent the data of the real network, and the empty squares represent the simulation result.

5 Effects of Communication Patterns on Firm's Social Network Structure

When proving the validity of the firm-growing model, we explored extensively the evolution of the firm's social network and the influence of communication patterns on network structure by investigating the dependence of clustering coefficient C , scalar and discrete assortativity on the model parameters β and P.

As presented in Fig. 4, C for fixed β monotonously increase with P, and C for fixed P monotonously and sharply decrease with β. Generally, it can be tuned in the range of $[0.20, 0.96]$. The clustering property of our model is tunable in a broad range by varying β and P, which makes it more powerful in modeling the real social networks.

As shown in Fig. 5, scalar assortativity coefficient for fixed β decreases with P but there is exception when $\beta = 0.01$ (appears as 0 in the graph), while scalar assortativity coefficient for given P decreases with β. For the value of β less than 0.3, the model generates assortative mixing networks, meanwhile the model also display disassortative mixing when the value of β is greater than 0.3.

Also as shown in Fig. 6, discrete assortativity coefficient for fixed β, increases with P, while discrete assortativity coefficient for given P decreases with β. We can note that the value of discrete assortativity coefficient is above zero, which demonstrates that the model produce the networks of assortative mixing within groups. And this simulation result is consistent with our general knowledge that the social network is positive correlation.

As mentioned in Section 2, the parameters β and P respectively represent the degrees to which individuals are reluctant to communicate within groups or across groups. In one case of lower value of β , individuals readily initiate the intra-group communication according to Equ. (3) and (4), which brings more

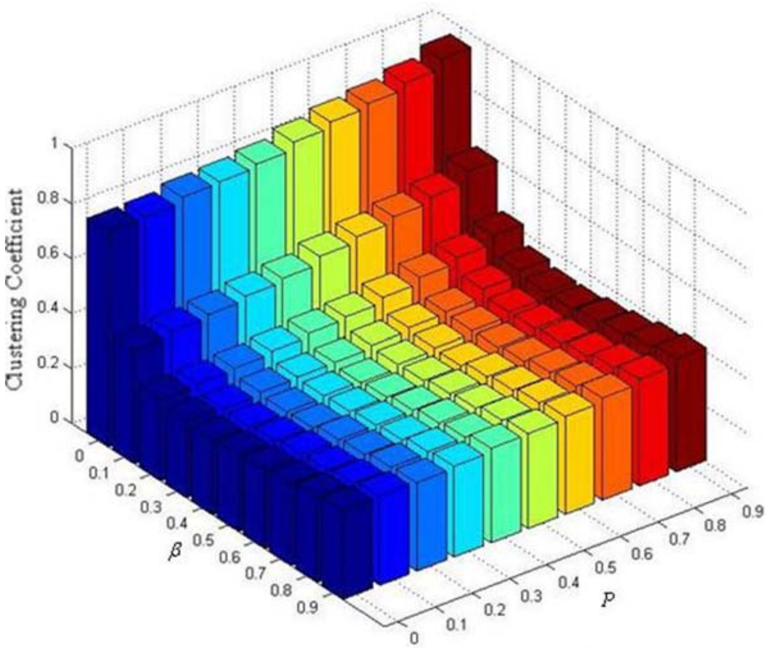

Fig. 4. Dependence of clustering coefficient on both β and P. The network size N=225. Simulation results are obtained by averaging over 500 different realizations.

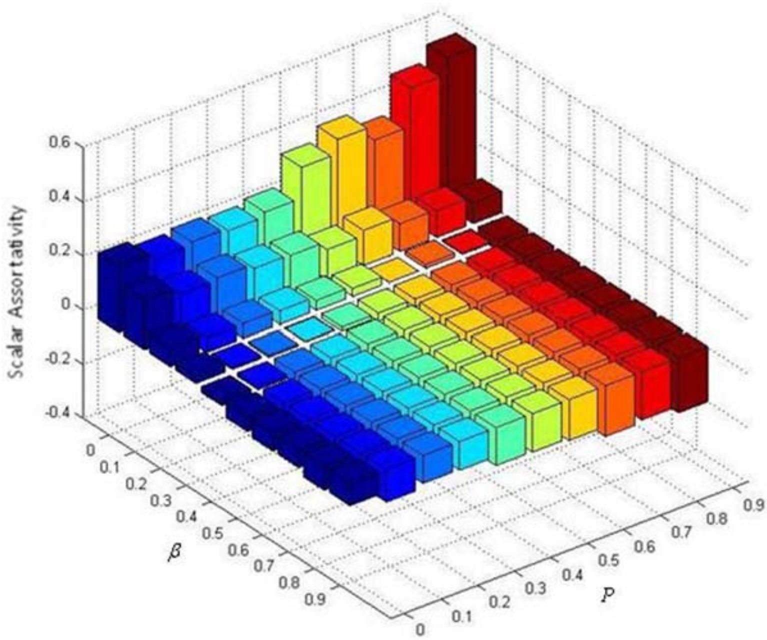

Fig. 5. Dependence of scalar assortativity coefficient on both β and P. The network size N=225. Simulation results are obtained by averaging over 500 different realizations.

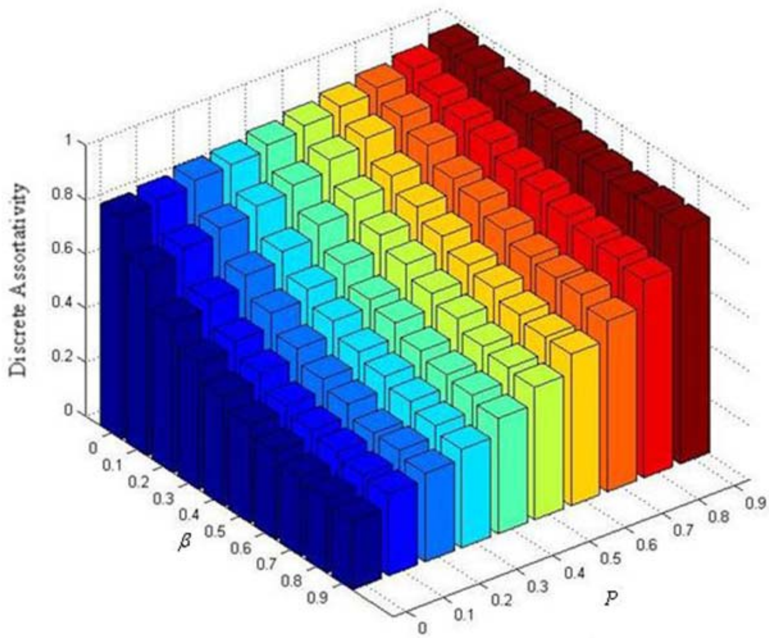

Fig. 6. Dependence of discrete assortativity coefficient on both β and P. The network size N=225. Simulation results are obtained by averaging over 500 different realizations.

chances for the employees of fewer neighbors to connect to those similar to them and results in a relatively larger value of clustering coefficient, and this is consistent with the positive value of scalar assortativity coefficient, which implies that employees with more neighbors tend to connect with those of more neighbors, and employees with fewer friends tend to connect with those of fewer friends. In the other case of higher value of β , due to the individuals' apathy to communicate within groups, there are few connections between those with fewer degrees, which leads to lower value of clustering coefficient, thus the value of scalar assortativity coefficient is negative, which reflects that employees with fewer neighbors tend to connect with those of more neighbors, and vice verse. When the value of P is low, the employees activate the inter-groups interactions, which leads to relatively low density of assortative mixing within groups, corresponding to the low value of discrete assortativity coefficient; while the value increases, the intension to communicate across groups declines to one extreme that only few employees participate the formal inter-groups communication, resulting in high density of assortative mixing within groups, namely high value of discrete assortativity coefficient. Actually in the real world of firms, especially the large manufacturers, as a result of bureaucracy and the divisions of departments, the inter-department communications are not advocated, and the intra-department interactions are not encouraged, or even if encouraged there are still some factors hindering communication, such as the organization silos and the physical distance [11][12], namely the values of β and P are relatively high, thus the scalar assortativity coefficient is negative and the discrete assortative coefficient is relatively larger, just as what we can note in Table 1. In contrast, the advantage of communication between scientists within the same field is relatively obvious. Many available platforms, such as the research association, annual international conferences, seminars, publications, personal website or blog, visiting position, bring about opportunities for scientists of the same discipline to interact with each other, corresponding to lower value of β and contributing to the positive scalar assortative coefficient, as demonstrated in [30].

6 Conclusion

Since the structure of firm's social network has crucial effect on the organization's knowledge creation, learning and transfer, which have been recognized as the source of organization's sustainable competence advantage, some researchers make efforts to identify the factors that influence the growth and structure of firm's social network, in order to obtain the guideline for management practice. However the traditional social research methods are unable to prove the cause-effect relationship between antecedents and structure of social network due to the weakness of cross-sectional data. However the development of complex network study offers another possibility to accomplish the task. In this article, we proposed the firm-growing model, and compared the simulation results with empirical data. The agreement of the simulation results and empirical data justified the validity of the model. And then we explored extensively the effect of communication patterns, represented by parameters of β and P, on the growth and structure of firm's social network. The theoretical contributions of this article are: first, this article helps to bridge a gap between the social network study and organization management practice, and finds that the extends to which individuals' reluctance to communicate within groups or across groups impact significantly the structure of firm's social network; second, this article is just one of few attempts to model the evolution of firm's social network, and the agreement between the simulation results and empirical data strengthens the validity of this model.

This research has limitations. The first limitation is that the network growth model only considered the addition of new employees and ignored employee's leaving the organization due to resignation or retirement. The second limitation is that, in the real world there are a number of factors driving the intra-group interactions, e.g. homophily, identity, physical proximity, and task-related; but in this network growth model we only considered the number of neighbors one has.

The future research can consider these two limitations and improve this firm's growing model. Actually there are other types of relationships, such as trust, friendship, energy relationship, and these types of relationships also play vital roles in the knowledge transfer and collaborations. The future study can dig more deeply into the firm's social network by focusing on these types of relationships.

References

1. Nonaka, I.: A dynamic theory of organizational knowledge creation. Organization Science 5(1), 14–37 (1994)
2. Drucker, P.: Post-Capitalist Society. Butterworth Heinemann, London (1993)
3. Granovetter, M.: The strength of weak ties. American Journal of Sociology 78, 1360–1380 (1973)
4. Burt, R.S.: Structural holes: the social structure of competition. Harvard University Press, Cambridge (1992)
5. Burt, R.S., Ronchi, D.: Teaching executives to see social capital: results from a field experiment. Social Science Research 36, 1156–1183 (2007)
6. Ramasco, J.J., Morris, S.A.: Social inertia in collaboration networks. Physical Review E 73, 016122 (2006)
7. Ebel, H., Mielsch, L.I., Borbholdt, S.: Scale-free topology of e-mail networks. Phys. Rev. E. 66, 35103 (2002)
8. Bachnik, W., Szymczak, S., Leszczynski, P., Podsiadlo, R., Rymszewicz, E., Kurylo, L., Makowiec, D., Bykowska, B.: Acta Phys. Pol. 36, 3179 (2005)
9. Csányi, G., Szendröi, B.: Structure of a large social network. Physical Review E 69(3), 036131 (2004)
10. Guimera, R., Uzzi, B., Spiro, J., Amaral, L.A.N.: Team assembly mechanisms determine collaboration network structure and team performance. Science 308, 697–702 (2005)
11. O'Dell, C., Grayson, C.J.: If only we kew what we know: indentification and transfer of internal best practices. California Management Review 40(3), 154–174 (1998)
12. Zalesny, M.D., Farace, F.V.: Traditional versus open offices: A comparison of sociotechnical, social Relations, and symbolic Meaning Perspectives. Academy of Management Journal 30(2), 240–259 (1987)
13. Katz, R., Allen, T.J.: Investigating the not invented here (NIH) syndrome: a look at the performancetenure and communication patterns of 50 R&D project groups. R& D Management 12(1), 7–19 (1982)
14. Anklam, P.: Knowledge management the collaboration thread. Bulletin of the American society for information and technology 28(6), 8–11 (2002)
15. Cummings, J.N., Cross, R.: Structural properties of work groups and their consequences for performance. Social Networks 25, 197–210 (2003)
16. Hansen, M.: The search-transfer problem: The role of weak ties in sharing knowledge across organizational subunits. Admin. Sci. Quart. 44, 82–111 (1999)
17. Szulanski, G.: Exploring internal stickiness: impedements to the transfer of best practice within the firm. Strategic Management Journal 17, 27–43 (1996)
18. Krackhardt, D., Hanson, J.R.: Informal networks: the company behind the chart. Harvard besiness review, 104–111 (July-August 1993)
19. Levin, D.Z., Cross, R.: The Strength of Weak Ties You Can Trust: The Mediating Role of Trust in Effective Knowledge Transfer. Management Science 50(11), 1477–1490 (2004)
20. Cohen, R., Erez, K., ben-Avraham, D., Havlin, S.: Resilience of the internet to random breakdowns. Physical Review Letters 85, 4626–4628 (2000)
21. Newman, M.E.J., Park, J.: Why social networks are different from other types of networks. Phys. Rev. E. 68, 036122 (2003)
22. Newman, M.E.J.: Mixing patterns in networks. Phys. Rev. E 67, 026126 (2003)
23. Erdös, P., Rényi, A.: On random graphs. Publicationes Mathematicae 6, 290–297 (1959)

24. Newman, M.E.J.: Assortative mixing in networks. Phys. Rev. Let. 89, 208701 (2002)
25. Amaral, L.A.N., Scala, A., Barthlmy, M., et al.: Classes of small-world networks. Proc. Natl. Acad. Sci. USA 97, 11149–11152 (2000)
26. Newman, M.E.J.: Scientific collaboration networks. I. Network construction and fundamental results. Phys. Rev. E 64, 016131(2001)
27. Zhang, P.P., Chen, K., et al.: Model and empirical study on some collaboration networks. Physica A: Statistical Mechanics and its applications 360(2), 599–616 (2006)
28. Chang, H., Su, B.B., Zhou, Y.P., He, D.R.: Assortativity and act degree distribution of some collabortation networks 383(2), 687–702 (2007)
29. Freeman, L.: Centrality in social networks: Conceptual clarification. Social Networks 1(3), 215–234 (1979)
30. Albert, R., Jeong, H., Barabási, A.-L.: Attack and error tolerance in complex nerworks. Nature 406, 387–482 (2001)