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Selection Method of Customer Partners in Customer Collaborative Product Innovation

Abstract: Partner selection is an important aspect of the customer collaborative product innovation process and aims to select innovative customer partners from huge numbers of customers, fast and accurately. The purpose of this article is to present a quantitative partner selection method based on the complex network theory. In this method, the complex network model of the Online Community Customer Network (OCCN) is constructed, and network centrality is used as the initial index of customer partner selection. Then, network efficiency and delta centrality are used to evaluate the effect of the index. An example is presented to reflect the feasibility and efficiency of the proposed method. Results validate the small-world and scale-free properties of the OCCN and show that betweenness centrality is the most appropriate index for partner selection in the OCCN.

Keywords: Partner selection, complex network, network centrality, efficiency, delta centrality.

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1 Introduction

The importance of customer collaborative product innovation (CCPI) has been recognized for many years [9]. Collaborative innovation with customers is increasingly important for the development of new products. Customers gradually become involved in the process of collaborative product innovation as the main innovation agents. The user-centered innovation process has more advantages and now becomes more popular than the manufacturer-centered innovation development system, which has been the mainstream for hundreds of years.

As a result, scholars have gained many achievements in their related researches on CCPI. Von Hippel [21] proposed the concept of customer innovation, analyzed the characteristics of lead users, and built the methodology framework. Payne et al. [18] proposed the value model of CCPI and provided a detailed analysis of the customer value-creating process. Etgar [5] constructed the conceptual framework of CCPI and designed six stages of collaborative innovation with customers' participation. Ojanen and Hallikas [17] studied driving and restricting forces, and improved the framework and process mentioned above. Yang et al. [29] proposed a three-dimensional integrated organization model based on the analysis of the innovative agents' features and the construction of the conceptual ontology model. Li and Yu [15] analyzed factors influencing the efficiency of CCPI and proposed an efficiency evaluation model based on improved wavelet neural network. Greer and Lei [9] summarized the research results of CCPI and provided an outlook on future research. The works are mainly focused on the theoretical discussion of CCPI. Many practical problems remain to be studied.

Not all customers need to participate in the CCPI process. CCPI is mainly carried out by lead users [21]. Hence, this part of the customers should be specifically identified and chosen as the customer partner by enterprises for carrying out CCPI. Through partner selection, these customers can participate in parts of the work such as innovation design and trial and error of new products. In addition, due to the limited resources of the enterprise, only part of our customers will be provided with resources for collaborative innovation activities. Therefore, the selection of customers as partners has become a significantly important element in CCPI, especially in practice.

However, there are few studies about the partner selection for CCPI. Von Hippel [21] defined "lead users" as individuals displaying two characteristics: (i) they face needs that will diffuse in a marketplace, but face them before the bulk of that marketplace encounters them, and (ii) they are positioned to benefit significantly by obtaining a solution to those needs. However, he did not provide a quantitative method for identifying lead users. Research by Bettencourt et al. [2] is relevant to partner selection, and they noted the importance of organizational citizenship behaviors such as helping behaviors and individual initiative. Wang et al. [24] constructed an evaluation index system for partner selection, and proposed the selection method of customer partners based on rough sets and support vector machine. In addition, Fuller et al. [8] have concluded that initiatives may sometimes be symbolic. The above works provide ideas for customer partner selection; however, four problems remain unsolved as follows. (i) The studies above are mainly based on qualitative description of the partners. No effective quantitative methods for partner selection have been proposed. (ii) To some degree, the selection methods based on evaluation methods such as rough sets are subjective, which reduces the accuracy of the selection. (iii) Advances in network technology have made the communications among customers occur mainly in the online community, which transfers the background of partner selection to the online community. (iv) Because of the huge number of customers in the online community, the above methods cannot be used to complete the customer partner selection fast and accurately. Thus, the problem is equivalent to selecting a customer partner from huge number of customers in the online community [16].

The complex network is the abstract of a complex system that reflects the relationships among elements in the complex system. The research of complex networks originates from the random graph theory and then is enriched due to the discovery of the small-world network [25] and scale-free network [1] models. The complex network theory provides a powerful tool to study complex features and analyze the evolution mechanism and dynamic characteristics of complex networks such as transportation networks, power grids, and collaborative production networks [10, 26, 28, 30]. It also provides a novel method of selecting a customer partner in the online community.

In this article, a network analysis approach for the selection of partners in CCPI is proposed. The article is organized as follows. In Section 2, the customer online community and its characteristics as a complex system are introduced, which build the foundation for selecting customer partners with the application of the complex network theory in the online community condition. In Section 3, the topology model of the Online Community Customer Network (OCCN) is constructed and the validation methods of "small-world effect" and "scale-free property" are proposed. Three kinds of network centricity indicators are introduced. An evaluation method of network centricity indices based on network efficiency and delta centrality is presented to select the suitable index for the OCCN. In Section 4, a case study is used to verify the feasibility and applicability of the proposed method. In Section 5, conclusions are provided and future research is discussed.

2 Complex Features Analysis of the OCCN

As mentioned above, communication among customers mainly occurs in the online community now. There exist complex relationships between customers in the online community in terms of information flow. The structural relationships between the customers constitute a complex network. Customers are the nodes of the network. Their connections and relevancies are the edges of the network. As a result, the OCCN is formed in the web environment.

OCCN has the basic characteristics of a complex system with the properties of being non-linear, open, dynamic, diverse, and uncertain [19]. First of all, customers in the online community interact with each other. Second, customers will take the initiative to strengthen contact with each other in order to obtain more external resources and knowledge, which accelerates the solution of the problems. This makes the behaviors of the OCCN more open. Third, dynamic changes in customer requirements, the development of advanced design tools, and the customers' own learning make the OCCN in constant movement. In addition, the diversity of the OCCN becomes evident because it consists of customers with various preferences and different characteristics. Finally, there are a large number of random and vague factors in the interaction process among customers of the OCCN.

3 Selection of Partners in CCI Based on the Complex Network Theory

3.1 Topological Structure and Basic Parameters of the OCCN

To verify the small-world and scale-free properties of the OCCN, its topological structure should be represented first. Then, the calculation method of the basic parameters of the OCCN will be introduced.

3.1.1 Representation of the OCCN Topology

The topology model of a network is the basis of the research in complex networks, which is the abstract of the complex system. When we describe the customer system in the online community with the application of the complex network theory, the topological structure chart of the OCCN needs to be generated first by using the software NetDraw to visualize the OCCN topology. Then, we can observe the topological structure of the OCCN and calculate the related parameters easily. To facilitate discussion in this article, the following assumptions about the network need to be made.

1. Customers in the online community are the nodes of the OCCN.
2. Communication relationships of information and knowledge among customers are the edges.
3. Take no account of individual differences between customers, so that the OCCN is unweighted.
4. Take no account of the direction of information flow between any two customers, which means that the OCCN is undirected.

Therefore, we express OCCN with the undirected and unweighted graph G.

$$G=(V,E), \tag{1}$$

where $V = \{v_1, v_2, \dots, v_n\}$ is the set of customer nodes and n is the number of customer nodes, and $E = \{(v_i, v_j)\}$ represents the set of links $e_{i,j} = (v_i, v_j)$. The link between i and j is the same as the one between j and i because of undirected network, as shown in Eq. (2):

$$(v_i,v_j)=(v_j,v_i). \tag{2}$$

The adjacency matrix $A = \{a_{i,j}\}$ is used to model the topological structure of OCCN as Eq. (3):

$$A_{n\times n}=\begin{bmatrix} a_{1,1} & \cdots & a_{1,n} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,n} \end{bmatrix}, \tag{3}$$

where $a_{i,j}$ denotes the communication relationship between customer v_i and v_j. Its definition is as shown in Eq. (4):

$$a_{i,j}=\begin{cases}1 & \text{there is communication relationship between } v_i \text{ and } v_j\\ 0 & \text{no communication relationship between } v_i \text{ and } v_j\end{cases}\quad 1\le i,j\le n. \tag{4}$$

3.1.2 Basic Parameters of the OCCN

In the past few years, many concepts have been formed in the description of the complex network topological features, among which four are basic concepts: degree, degree distribution, average path length, and clustering coefficient. Degree and degree distribution reflect the scale-free characteristic of the network. The average path length and clustering coefficient reflect the small-world property of the complex network. On the basis of the description above, we interpret the significance of the four concepts in the OCCN as follows [11].

3.1.2.1 Degree and Degree Distribution

Degree $k(i)$ of node i is defined as the number of nodes or edges with which node i directly connects:

$$k(i)=\sum_{j=1}^{n} e_{i,j}. \tag{5}$$

Degree, which describes the direct influence of nodes in the static network, is a simple and important concept for a single node of the complex network. In the OCCN, the degree of a network node is the number of customers who have a direct link with the customer. As a result, degree represents the direct social relations of customers in the OCCN. Therefore, a greater degree of a customer implies a stronger direct social relation.

Studies show that topological structure properties and dynamic behavior in complex networks are both dependent on the degree distribution of the complex network. Degree distribution is commonly modeled by the distribution function $P(k)$, which is the probability that a randomly selected node i has exactly k_i edges. Specifically, $P(k)$ is the percentage of nodes with degree k out of all the nodes.

3.1.2.2 Average Path Length

The average path length L, a measure of the global structure of the graph, also known as "the shortest path length," is defined here as the average number of edges that must be traversed in the shortest path between any two vertices in the graph. In terms of Milgram's experiment, L is the chain length averaged over all possible sources in the network and all possible targets [22]. It could be calculated with the Floyd algorithm as

$$L=\frac{1}{n(n-1)}\sum_{i\ge j} d_{ij}, \tag{6}$$

where d_{ij} is the distance between nodes i and j in the network or, in other words, the number of edges connecting the two nodes in the shortest path. In the OCCN, the average path length L measures the transmission performance and connectivity between customers in the OCCN.

3.1.2.3 Clustering Coefficient

Contrary to the average path length L, the clustering coefficient reflects the local structure features of the network. Suppose that the degree of node i in the network is k_i. Then, among the k_i nodes, the number of edges is no more than $k_i(k_i-1)/2$. Thus, we define the clustering coefficient C_i of node i as

$$C_i=\frac{2EN_i}{k_i(k_i-1)}, \tag{7}$$

where EN_i is the number of edges really existing among those k_i adjacent nodes of node i.

The clustering coefficient C of the whole network is the average value of the clustering coefficient C_i of all nodes i, namely

$$C=\frac{1}{n}\sum_{i}^{n}C_i. \tag{8}$$

The clustering coefficient measures the collectivization degree of the network. It hence can be used to measure the collectivization degree of customers in the OCCN.

3.2 Verification of the Topological Features of the OCCN

Verification of topological features is the premise of using the complex network method. Empirical research shows that the small-world effect and scale-free property are the most fundamental characteristics of complex networks. Most of the actual complex networks have both scale-free and small-world characteristics [27]. Therefore, we introduce topological features and their verification methods by introducing the two characteristics first.

3.2.1 Small-World Characteristic

In 1998, to describe the transition from a regular network to a random graph, Watts and Strogatz [25] introduced the concept of the small-world network based on the human social network model. An interesting popular manifestation of the "small-world effect" is the so-called six degrees of separation principle, suggested by a social psychologist, Milgram, in the late 1960s [22].

A small-world network possesses the basic characteristics of a smaller average path length, L, and a larger clustering coefficient, C. The clustering coefficient can be used to measure the aggregation degree. The transmission performance and connectivity between the nodes of a network can be measured by the average path length. The smaller the average path length is, the higher the efficiency of the small-world network is.

Studies have shown that the Web, film actors, general social networks, and so on, have small-world properties. The network possesses the characteristic of being small world if the clustering coefficient of the network is much greater than that of an equivalent random one, i.e., $C >> C_{\text{ran}}$, while their path lengths are approximately equivalent, i.e., $L \approx L_{\text{ran}}$. To verify the small-world characteristic of the network, a method was proposed and verified by Sporns et al. [20]. The method can be generalized as shown in Eq. (9):

$$\frac{C}{C_{ran}}>\frac{L}{L_{ran}}. \tag{9}$$

The parameter C_{ran} is created in the random network mentioned above, and C can be calculated by using the software Ucinet [3]. L is the average path length and L_{ran} is the one in the corresponding random network. The Floyd algorithm can be introduced to solve the average path length, as shown in Eq. (6).

3.2.2 Scale-Free Property

Following the discovery of the small-world characteristics, Barabasi and Albert [1] from the Physics Department of Norte Dame, an American University, tracked and studied the dynamic evolution of the World Wide Web. They assumed that HTML documents are nodes of network, and hyperlinks among documents are the edges. They also found that the degree distribution of the World Wide Web followed a power-law distribution as

$$P(k)\sim k^{-\gamma}, \tag{10}$$

where γ is the scale of the network and $\gamma \in (2, 3)$. Different networks have different scale values. Networks that follow a power-law distribution are called scale-free networks because they are scale invariant. In addition, two basic principles were also proposed by Barabasi and Albert at the same time in order to reveal the origin of power-law degree distribution: (i) growth property: the nodes of the network are increasing with time; (ii) optimal connectivity: a new node will give priority to connecting with nodes with higher connection degrees. The scale-free characteristic of a complex network is mainly manifested in the following three aspects: (i) the vast majority of nodes have only a few number of connections; (ii) a handful of nodes have a large connection number of edges; (iii) a handful of nodes constitute the hub of communications in the network and the efficiency of information transmission is very high.

The method of verifying the scale-free property of OCCN is to calculate the degree distribution and examine if it fits a power-law distribution as mentioned in Eq. (10). For the ease of calculation, the degree distribution in the double-logarithmic coordinates is usually examined. If there is a linear relationship between $\log P(k)$ and $\log(k)$ as

$$\log P(k) = -\gamma \log k + a, \tag{11}$$

the degree distribution of this network has a power-law feature and the network exhibits a scale-free feature.

3.3 Centrality of the OCCN

The centrality of complex networks is used to measure the centralization degree of nodes in the network. The centrality measure of complex networks has contributed to the discovery of important nodes fast and accurately in large-scale complex systems. Currently, there are >11 centrality indices in the application, including degree centrality (DC), closeness centrality (CC), betweenness centrality (BC), eigenvector centrality (EC), flow betweenness centrality (FBC), and so on [4]. Three of them are the most commonly used: DC, CC, and BC [10].

3.3.1 Common Centrality Indices

3.3.1.1 Degree Centrality

DC is the simplest centrality measure index. The node degree can be calculated according to Eq. (5). As mentioned above, DC describes the direct influence of static nodes in the network and investigates customers' direct social relationship in an OCCN.

To use DC to measure network centricity, the values of DC need to be normalized. The maximum degree value of a network with n nodes is $n - 1$; therefore, DC after normalization is defined as

$$\mathrm{DC}(i) = \frac{k(i)}{n-1}. \tag{12}$$

3.3.1.2 Closeness Centrality

CC is used to measure the difficulty the node has in arriving at the other nodes in the network, and is often used in social network [7]. In an OCCN, CC examines the indirect influence and social relations of customers through the network. The CC value of a node is defined as the reciprocal of the sum of the distances between the node and the others. Specifically

$$C(i) = \left[\sum_{j=1}^{n} d_{ij}\right]^{-1}. \tag{13}$$

The minimum value of the sum of the distances from node *i* to the other nodes is $n-1$ for a network with n nodes. Thus, CC after normalization is defined as

$$\mathrm{CC}(i)=(n-1)C(i)=(n-1)\left[\sum_{j=1}^{n} d_{ij}\right]^{-1}. \tag{14}$$

3.3.1.3 Betweenness Centrality

BC depicts the influence of nodes on information flow and the possibility that information flows through the node. The values of BC will increase with the increase of information flow of the nodes. In OCCN, BC examines the social acceptability of customers and their influence on the information flow in social network. The BC index is defined by Freemann [6] as

$$B(i)=\sum_{s\neq t\neq 1}\frac{g_{s,t}(i)}{g_{s,t}}, \tag{15}$$

where $g_{s,t}$ is the number of the shortest paths between the nodes *s* and *t*, and $g_{s,t}(i)$ is the number of shortest paths linking the two nodes *s* and *t* containing node *i*.

For a given node *i*, the betweenness of the node takes the maximum value when all the shortest paths between any two other nodes pass through the node *i*. Therefore, the maximum betweenness of the node is $(n-1)(n-2)/2$. BC after normalization is defined as

$$\mathrm{BC}(i)=\frac{2B(i)}{(n-1)(n-2)}. \tag{16}$$

3.3.2 Evaluation of Centrality Measure Indices

In the preceding section, the three most commonly used centrality indices are introduced. Each index has various effects for different network topologies. Thus, it will be necessary to evaluate the effect of the three indices in order to choose the most appropriate one to achieve the customer partner selection in OCCN.

To assess the applicability of the centrality indices, Freeman [6] established the integrated centrality formula and defined the comprehensive centrality degree. However, the evaluation method is complex and does not directly reflect the applicability of the indices. Latora et al. [13, 14] presented an evaluation method based on network efficiency and delta centrality.

The concept of network efficiency was proposed for measuring the efficiency of information exchange between two nodes [13]. The efficiency is defined as the reciprocal of the shortest path length d_{ij} between two nodes, as shown in Eq. (17):

$$ne_{ij}=\frac{1}{d_{ij}}. \tag{17}$$

The global network efficiency is calculated as the average over the efficiencies of all nodes, as shown in Eq. (18):

$$NE=\frac{1}{n(n-1)}\sum_{i\neq j\in G} ne_{ij}=\frac{1}{n(n-1)}\sum_{i\neq j\in G}\frac{1}{d_{ij}}. \tag{18}$$

Delta centrality is based on the following idea: the importance of a node (group of nodes) is related to the ability of the network to respond to the deactivation of the node (group of nodes) selected by the centrality indices from the network [14]. In this article, the evaluation method based on network efficiency and delta centrality is proposed to compare network efficiencies under the three indices when the customer nodes selected by the indices are deactivated. Then, the centrality index with the most variable network efficiencies will be chosen as the index of customer partner selection. The method can be expressed by Eq. (19):

$$\phi(\{\mathrm{CI}_j\},\{V_j\})=\frac{\Delta NE(\mathrm{CI}_j,V_j)}{NE}=\frac{NE-NE(\mathrm{CI}_j,V_j)}{NE},0\le\phi\le1, \tag{19}$$

where $\{\mathrm{CI}_j\}$ is the set of centrality indices and CI_1 = DC, CI_2 = CC, CI_3 = BC; $\{V_j\}$ is the set of customer partners selected by centrality index CI_j; *NE* denotes the initial efficiency of the OCCN; and $NE(\mathrm{CI}_j, V_j)$ is the efficiency after the deactivation of the customer nodes selected by the centrality index CI_j.

3.4 Process of Customer Partner Selection for CCI

Through the analysis, the flow chart can be shown as in Figure 1.

The specific process of customer partner selection is described as follows.

Step 1. Collect the data of relationships among the customers in the online community.

Step 2. Establish the adjacency matrix *A* and draw the topology diagram *G* of the OCCN.

Step 3. Calculate the basic topological parameters of the OCCN according to Eqs. (5) to (8).

Step 4. Verify the small-world effect according to Eq. (9) and the scale-free property according to Eq. (11). Then, analyze the complex topological characteristics of the OCCN. If the OCCN has one of the properties above, proceed to the next step; otherwise, the method is not inapplicable and stop.

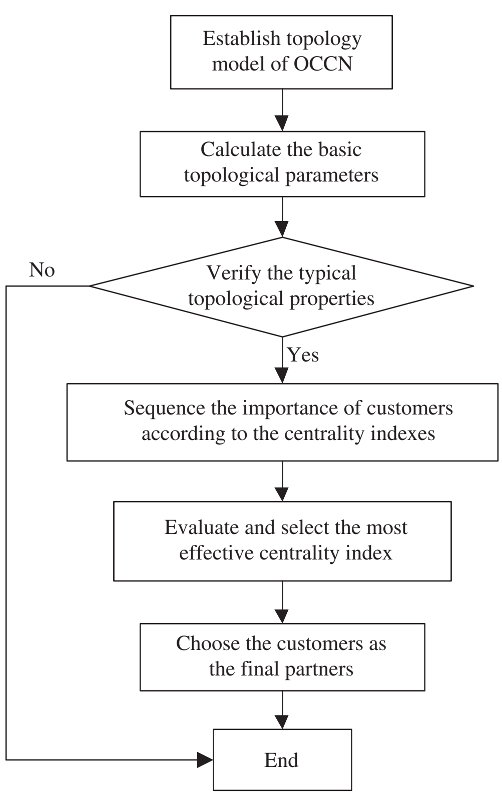

Figure 1. Flow Chart of Customer Partner Selection.

Step 5. Sequence the importance of customers according to the DC index, which is calculated by Eqs. (5) and (12), and select the innovative customer partners.

Step 6. Sequence the importance of customers according to the CC index, which is calculated by Eqs. (13) and (14), and select the innovative customer partners.

Step 7. Sequence the importance of customers according to the BC index, which is calculated by Eqs. (15) and (16), and select the innovative customer partners.

Step 8. Evaluate and compare the applicability of the three centrality evaluation indices based on network efficiency and delta centrality according to Eqs. (18) and (19).

Step 9. Select the most effective centrality index as the index of customer partner selection in the OCCN and choose the customers as the final partners based on this indicator for CCI.

4 Case Study

There is a well-known company that has constructed its own online community and employed customer collaborative product innovation. The case study involves a sample of customers of the company in the online community. Taking all factors, such as cost and the company's scale, into consideration, the company plans to choose 10 innovative customer partners to verify the above partner selection method. According to the statistics of the connections among 563 online community customers, we eliminated 87 customers who have not carried out any exchange activities, such as posting of messages or comments after registration. Thus, there are 476 nodes and 950 edges in this OCCN. After the statistics, we established adjacency matrix *A* and used Ucinet to draw the topological structure of OCCN, as shown in Figure 2.

4.1 Verification and Analysis of the Small-World Characteristic

In this article, the software Ucinet was first used to generate the *ER-random network*, which has the same scale as the OCCN. Then, the average path length and clustering coefficient were calculated separately. The results of computation are shown in Table 1.

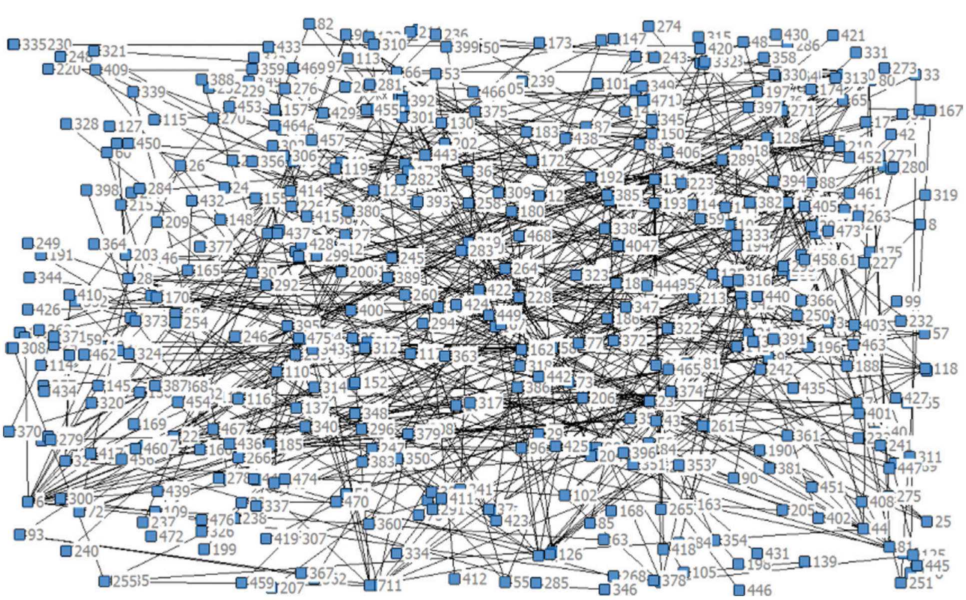

Figure 2. Topology Structure of the OCCN.

Table 1. Comparison between the OCCN and the *ER-Random Network*.

Node	Network density	OCCN		*ER-random network*		Comparison	
		C	L	C_{ran}	L_{ran}	C/C_{ran}	L/L_{ran}
476	0.0493	0.1996	2.9012	0.0141	3.0216	14.1560	0.9602

Through the comparison above, we can see that the average path length L of the OCCN corresponds to that of the random network, while the clustering coefficient is far greater than that of the random network. According to $\frac{C}{C_{ran}} > \frac{L}{L_{ran}}$, the OCCN has the small-world characteristic.

Generally speaking, the short average path length in the small-world network reflects the high exchange efficiency of information such as knowledge between nodes. The shorter the average path length is, the higher the efficiency will be. Moreover, a large clustering coefficient reflects a high collectivization degree of the network [12]. On the one hand, the fact that OCCN has the small-world characteristic shows that the relationship between the customers is close and the efficiency of information exchange is high. On the other hand, a high cluster degree of the OCCN can promote the spread of information and contribute to the promotion of new products and the solution of customers' problems.

4.2 Verification and Analysis of the Scale-Free Property

According to Eq. (11), the degree distribution of the OCCN was calculated, and we found that log(P(k)) and log(k) were co-linear and log(P(k))= –2.153 log(k) + 5.7683. The log-log plot generated in Matlab is shown in Figure 3. Therefore, we conclude that the OCCN is a scale-free network.

Two conclusions about the OCCN can be drawn as follows from the value of the degree distribution and the scale-free feature of the complex network [23]:

1. In OCCN, there are a few core customers who play an important role in the online community and grasp the customer demands quickly and accurately through contact with other customers.

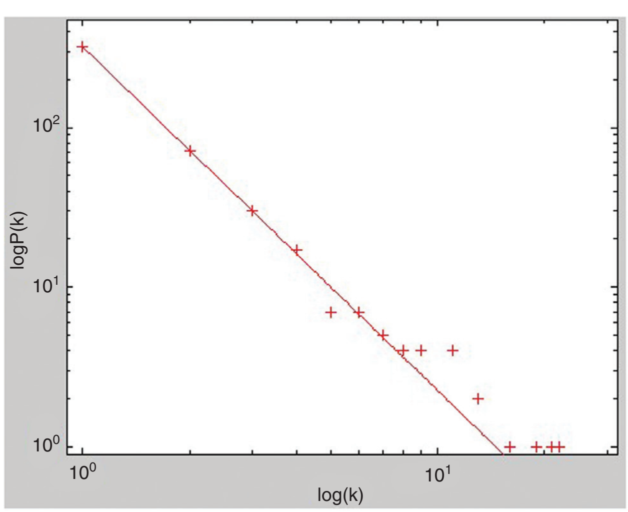

Figure 3. Degree Distribution of the OCCN on the Dual-Logarithmic Coordinate Diagram.

2. The scale is small while the edges are many, so the OCCN is close to the complete network. Therefore, information exchange between various customers is relatively broad and their coupling relationships are strong.

4.3 Selection of Customer Partners

First of all, we rank the customers' importance according to the degree centricity calculated by Eqs. (5) and (12), and choose the top 10 as innovative customer partners. Then, we rank it according to the CC of Eqs. (13) and (14), and also choose the top 10 as partners. Finally, we rank it under the BC according to Eqs. (15) and (16), and also select the top 10 as partners. The evaluation results of three centricity indices and partners selected by the indices are as shown in Table 2.

It can be seen from Table 2 that there exist huge gaps between the results evaluated by DC and the other two indices, while the results evaluated by CC and BC are basically the same. As a result, the accuracy of CC and BC are higher according to our primary evaluation. Next, the network efficiency and DC will be used to quantitatively assess the effect of the three centrality indices.

According to Eq. (18), the initial network efficiency E of the OCCN is 0.1677. Then, we attack the customer nodes selected by the three centrality measure indices, respectively. In other words, we make the 10 customer nodes invalid. The value changes of network efficiency of the OCCN have been calculated in these three situations, as shown in Table 3.

From the data of Table 3, certain generalizations can be made. (i) Of the central nodes, 2.1% control at least 19% of the initial efficiency of the network, and the centralization effect of the OCCN is significant. In addition, a few important customer nodes have great influence on the OCCN and it corresponds to the statistical property of the scale-free network. (ii) In centrality indices, BC is more apparent for OCCN, which is different from the statistical results of traditional scale-free networks. The difference is because OCCN has both small-world and scale-free properties. (iii) It is more appropriate to use BC as the evaluation index of innovative customer partner selection.

Table 2. Partners Selected by Three Centricity Measure Indices.

DC (%)	Partners	*CC* (%)	Partners	*BC* (%)	Partners
4.632	16	25.469	1	69.809	1
4.421	6	25.306	2	63.845	2
4.000	1	22.207	4	38.441	4
3.368	58	22.145	16	38.200	16
2.737	4	21.899	6	31.565	6
2.737	12	21.522	5	25.109	5
2.316	3	21.139	7	18.808	3
2.316	2	20.679	58	18.355	23
2.316	23	20.360	90	17.907	7
2.316	32	20.360	218	13.738	32

Table 3. Change of Network Efficiency of the OCCN by Three Centrality Indices.

Initial (%)	Partner selection mode	After invalid (%)	Decline in proportion (%)
16.8	DC	15.5	7.74
	CC	15.8	5.95
	BC	13.6	19.0

5 Conclusions

Network centrality is an important concept for many applications. Most existing studies are focused on the choice of indices. In practice, network topology characteristics should be verified as the foundation of the application first. In addition, a quantitative comparison should be carried out.

In this article, we presented the concept of the OCCN, constructed its topology model, and analyzed its basic parameters. Our design principle is based on the complex network theory. Centrality measure indices of complex networks are used to complete the partner selection. Finally, a case study is shown to verify the feasibility and applicability of the proposed method. Our conclusions are as follows. (i) The OCCN has both small-world effect and scale-free property. The network centrality theory of complex networks can hence be used to select the customer partners. (ii) The relationships between the customers are close, and the efficiency of information exchange is high because of its small-world effect. (iii) There are heterogeneities among customer nodes, and the network centricity of the OCCN is more apparent because of its scale-free property. (iv) BC is the most appropriate index for the customer partner selection.

Our approach is easy to implement because the data of relationships between customers in the online community can be obtained easily, although some necessary assumptions are made. As part of this ongoing study, we plan to analyze the influences of the strength of the association among customers and employ more advanced techniques to improve the accuracy of customer partner selection.

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Bibliography

[1] A. L. Barabasi and R. Albert, Emergence of scaling in random networks, *Science* **286** (1999), 509–512.
[2] L. A. Bettencourt, A. L. Ostrom, S. W. Brown and R. I. Roundtree, Client co-production in knowledge-intensive business services, *Calif. Manag. Rev.* **44** (2002), 100–128.
[3] S. P. Borgatti, M. G. Everett and L. C. Freeman, *Ucinet for windows: software for social network analysis*, Analytic Technologies, Harvard, MA, 2002.
[4] E. Costenbader and T. W. Valente, The stability of centrality measures when networks are sampled, *Soc. Networks* **25** (2003), 283–307.
[5] M. Etgar, A descriptive model of the consumer co-production process, *J. Acad. Market. Sci.* **36** (2008), 97–108.
[6] L. C. Freemann, A set of measures of centrality based on betweenness, *Sociometry* **40** (1977), 35–41.
[7] N. E. Friedkin, Theoretical foundations for centrality measures, *Am. J. Sociol.* **96** (1991), 1478–1504.
[8] J. Fuller, H. Muhlbacher, K. Matzler and G. Jawecki, Consumer empowerment through Internet-based co-creation, *J. Manag. Inform. Syst.* **26** (2009), 71–102.
[9] C. R. Greer and D. Lei, Collaborative innovation with customers – a review of the literature and suggestions for future research, *Int. J. Manag. Rev.* **14** (2012), 63–84.
[10] R. Guimera, A. Llorente, E. Moro and M. Sales-Pardo. Predicting human preferences using the block structure of complex social networks, *Plos One* **7** (2012), 1–7.
[11] C. Kiss and M. Bichler, Identification of influencers – measuring influence in customer networks, *Decis. Support Syst.* **46** (2008), 233–253.
[12] C. Kuhnert, D. Helbing and G. B. West, Scaling laws in urban supply networks, *Physica A – Stat. Mech. Appl.* **363** (2006), 96–103.
[13] V. Latora and M. Marchiori, Efficient behavior of small-world networks, *Phys. Rev. Lett.* **87** (2001), 1–5.
[14] V. Latora and M. Marchiori, A measure of centrality based on network efficiency, *New J. Phys.* **9** (2007), 188–198. DOI: 10.1088/1367-2630/9/6/188.
[15] F. Li and Y. Yang, Efficiency evaluation of customer collaborative product innovation based on PSO-WNN, *Metalurgia Int.* **17** (2012), 118–124.

[16] G. Marchi, C. Giachetti and P. de Gennaro, Extending lead-user theory to online brand communities: the case of the community Ducati, *Technovation* 31 (2011), 350–361.
[17] V. Ojanen and I. Hallikas, Inter-organisational routines and transformation of customer relationships in collaborative innovation, *Int. J. Technol. Manag.* **45** (2009), 306–322.
[18] A. F. Payne, K. Storbacka and P. Frow, Managing the co-creation of value, *J. Acad. Market. Sci.* **36** (2008), 83–96.
[19] S. S. Qin, *The conception of complexity technology*, China Social Sciences Press, Beijing, 2004.
[20] O. Sporns, C. J. Honey and R. Kotter, Identification and classification of hubs in brain networks, *Plos One* **2** (2007), 1–14.
[21] E. Von Hippel, Lead users: a source of novel product concepts, *Management Science* **32** (1986), 791–805.
[22] X. F. Wang and G. R. Chen, Complex networks: small-world, scale-free and beyond, *Circuit Syst. Mag.* **3** (2003), 6–20.
[23] L. Wang and G. Z. Dai, Research on degree distribution of complex network, *J. Northwestern Polytech. Univ.* **24** (2006), 405–409.
[24] W. L. Wang, Y. Yang, M. K. Wang and L. J. Song, RS and SVM-based partner selection research for customer collaborative innovation, *Comput. Eng. Appl.* **43** (2007), 245–248.
[25] D. J. Watts and S. H. Strogatz, Collective dynamics of ‘small-world’ networks, *Nature* **393** (1998), 440–442.
[26] D. Q. Wei, X. S. Luo and B. Zhang, Analysis of cascading failure in complex power networks under the load local preferential redistribution, *Physica A – Stat. Mech. Appl.* **391** (2012), 2771–2777.
[27] J. S. Wu and Z. R. Di, Complex networks in statistical physics, *Prog. Phys.* **24** (2004), 18–46.
[28] X. H. Yang, G. Chen, B. Sun, S. Y. Chen and W. L. Wang, Bus transport network model with ideal n-depth clique network topology, *Physica A – Stat. Mech. Appl.* **390** (2011), 4660–4672.
[29] Y. Yang, Q. S. Xing, A. J. Liu, L. C. Wang, G. D. Yu, J. Z. Xie, Organization model and coordination efficiency in customer collaborative products innovation, *Comput. Integr. Manuf. Syst.* **18** (2012), 719–728.
[30] F. Zhang, Y. Yang, J. G. Jia, J. T. Wang, Topological characteristics of industry collaborative production networks, *J. Chongqing Univ.* **35** (2012), 21–27.