研究開発プロジェクトのイノベーション環境に関する社会ネットワーク分析

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R&D Network Analysis Based on Joint Applications in Lithium-ion rechargeble Batteries

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We analyzed the network structure surrounding an R&D project to explore external factors that contribute to the success or failure of a company's R&D project. In considering the network structure, we considered a small-world network. The reason for this is that the small-world network is characterized by the following three points:

1. The density of strings (chute) (which corresponds to the linear part of the network) is low.
2. The average path length (the length of the shortest path between two possible points on the network = the average number of steps) is short.
3. The connection between points is not complete. The three points can be summarized as follows.

In this paper, we take the lithium-ion rechargeable battery co-patent network as a case study to clarify how the R&D network changes over time and further discuss how the role of each node in the network becomes clearer.

keyword　Social Network Analysis, Graph Theory, Management of Technology

1. Introduction

The word "Network" is standard daily today. The word "network" is used in the network industry, and ICT-related network management, such as computer networks represented by the Internet, is not necessarily limited to computer networks. A concept is also used to understand human relationships, such as network society, regional networks, social networks, etc. Similarly, companies as legal entities also form networks connected by business-to-business relationships such as financial transaction networks, distribution networks, and parts/material procurement networks. The new product/business development or research and development fields are not also simply closed within the company. In addition to the network between various departments within the company, the procurement of raw materials and parts outside the company and customers. It forms a network of mutual relationships with related parties such as product evaluation feedback, companies other than the company (large companies, SMEs, venture companies), research institutes, and universities. R&D project success/failure factors are complexly related to internal or internal/external projects and 3C factors (customers, companies, and competitors). These form a network system that correlates with each other.

The R&D process has a step by step from many ideas to proof of concept, concrete technology verification, market verification, prototype evaluation, large-scale mass production, and commercialization. By deciding GO / NOT GO for each step, it is expected to increase the commercialization success rate. New product/new business development is carried out with complex interrelationships by many stakeholders, and in addition, due to recent open innovation activities, it goes beyond the areas and fields that companies have traditionally understood well. Collaboration outside the company is being carried out in unknown areas and fields. Despite the vital role of R&D, new business development project leaders

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who manage the whole project and their superiors, it is imperative to grasp the whole picture and appropriately determine where the problem lies. It is not possible to fully understand the whole, and it is supposed to make a judgment from local information. If we can correctly understand the appearance of the network between the parties involved in such research and development, we can grasp the whole picture and understand where the problems are. As a result, concrete actions can be taken to solve the problems, and as a result, it is expected that the commercialization of new products and new business development will be accelerated. In other words, by examining the correlation of R&D project performance indicators, we can classify the success or failure of our R&D project and predict the future of our ongoing R&D project.

From the past, in business administration, the network structure has been discussed using a conceptual, qualitative model. Research concerning new product development (NPD) began in the late 1960s when attempts were made to extract the success factors from each NPD success. One of the well-known research projects was the SHAPPO (scientific activity predictor from patterns of heuristic origins) project led by Freeman and Rothwell (C. Freeman 1988; Rothwell et al. 1974) and *"the NewProd project"* led by R.G. Cooper (Cooper 1979, 1983). Otherwise, few studies have identified these networks from objective, publicly disclosed data. Its reason is very simple. It was difficult to obtain large-scale data through the Internet until recent years, and computers had not enough ability to process the amount of data and analyze points of view about the network. However, we have become ready for large-scale massively parallel computing using GPUs, TPUs, and other special computational units in recent years. As a result, we can now perform social network analysis using large-scale data using relatively inexpensive computers. This work clarifies the relationship between the network structure index and the performance index in the R&D project from the disclosed large-scale data.

In general, R&D projects involve many factors, and when viewed globally, they make large-scale complex networks and are difficult to interpret for us. In order to classify the clusters into a typical pattern and interpret it qualitatively, we need to construct the mathematical model and consider how we understand the network structure in R&D project and its environmental factors. In this work, we tried that the environment of 612 R&D projects could be expressed in a small world(Milgram 1967). The basic idea for our approach is that R&D innovation can be influenced by creativity and performance. Previous studies have revealed that the network form that expresses one form of such a social organization is a small-world network. Previous research has quantitatively explained various networks, such as the small world of creative artists who produced Broadway musicals(Uzzi and Spiro 2005; Rivera, Soderstorm, and Uzzi 2010) and connections between companies using these models. Unlike many other common network structures, small-world networks are known to have highly and locally clustered networks, short path lengths, and two normally divergent network characteristics.

2. Methodology

This study aims to determine the relationship between innovation and the structure and performance of inter-firm networks for firms.

Mathematically, relationships between adjacent elements can be expressed using "graphs". In general, a graph is represented as a set of points (called vertices in graph theory) connected in some way by a set of lines (called edges in graph theory). In social network science, graphs allow us to represent the different types of networks we are interested in. In a graph, vertices represent elements of a network, and edges can represent defined relationships among connected elements.

2.1 Network Analysis

Granovetter has researched social networks on the "strength of weak ties" where novel and valuable information is more likely to come from people with weak social ties, such as acquaintances of acquaintances or people who know each other briefly (weak It is more likely to come from people with weak social ties (weak ties), such as acquaintances of acquaintances, or people with little acquaintances (weak ties), than from people with strong social ties (strong ties), such as one's own family, close friends, or workmates(Granovette 1973). In particular, Nieminen proposed order centrality, a concept in social network analysis, showing that order centrality is a valuable method for measuring graph centrality(Nieman 1973). Boissevain conducted a network analysis of how humans interact, share information, and conduct economic transactions in a village on the island of Malta (Boissevain 1974). Freeman defined proximity centrality as measuring proximity centrality by calculating the sum of the distances between a node and all other nodes and taking its reciprocal(L. C. Freeman 1977). This definition is still used today as one of the central indicators of social network analysis, such as mediate centrality proposed by Freeman(L. C. Freeman 1978). Mediocentricity is a measure of the extent to which a node plays a mediating role when it needs to take the shortest path between other nodes in the network. In other words, it indicates whether the node has is essential in transmitting information and diffusion of influence in the network. Coleman argued in the 1980s and 1990s that linkages among member in closed networks where information and resources are shared are desirable(Coleman 1988). Watts and Strogatz, on the other hand, proposed the Small World Theory(Watts and Strogatz 1998) in 1998, pointing out the importance of short-distance connections in social networks. Burt, in his work on the network structure of innovation creation(Burt 1992), found that networks with structural holes are more likely to have information redundancy than networks with sparse connections. Since the 2000s, Fleming has analyzed collaborative networks among inventors in patents and found that the structure of inventor networks is also an important factor in facilitating the propagation of new ideas and knowledge. Fleming also found that a dense inventor network may facilitate information and knowledge sharing(Fleming, Mingo, and Chen 2007). He also points out that when there is a central inventor, it is easier for information and knowledge to spread through that inventor. He also demonstrated the relationship between network structure and performance. Takashi has conducted empirical research on network structure and its impact on R&D and innovation performance(Kishi 2008). In recent years, social network analysis has been applied to business and economic fields, such as online networking and recent coronary infections due to the spread of social networking services. Against this background, However, there has not yet been enough empirical research on how to construct a forum for the creation of "knowledge" that is useful in practical terms.

2.2 Research Framework

This study used the Patent Information Platform (J-PlatPat) to analyze technical trends related to Lithium-ion Batteries. Of the patent information using the word "Lithium-ion Batteries" in the full text of the patents, 1967 patents that were made known after 2003, when the Lithium-ion Batteries culture system was established, were included in the analysis.

In this work, we derived three different concepts of centrality to estimate network properties. The first one is eigenvector centrality. The simplest form of centrality is the degree at a node. However, the degree is an extremely crude measure of centrality. In effect, it gives one "centrality point" for each neighborhood a node has. However, not all neighbors are necessarily equal. Often, a node's importance in a network is increased by having connections to other nodes that are themselves important. We can see the eigenvector centrality using the node's several points proportional to the centrality score of its neighbors rather than one point for each neighbor in the network it has. The graded equation is given as

$$u(t+1) = Au(t) \tag{1}$$

where A and $u(t) \equiv (u_1, u_2, \cdots, u_n)^T$ are the neighbor matrix and the vector aligned the centrality u_i of the node v_i respectively.

Interpreting the above equation as the influence u_i of a node is the sum of u_j over adjacent points, we can regard variable t as the index of updates for the iteration. Since the above equation is an incremental equation with t as the index, we consider repeating it to find the centrality at each vertex. In general, however, it is not possible to find the number of updates for $u_1, u_2, \cdots, u_N$ diverges. Therefore, we impose a bound condition each time such that the sum of $u_1, u_2, \cdots, u_N$ is equal to 1, and iterate. The linear algebra show us that these iterations are shown to be maximal eigenvectors of A if there is at least one closed odd angle in the network. Therefore, if the largest eigenvalue of A is λ_N, eigenvector centrality is given as

$$Au = \lambda_N u \tag{2}$$

N is natural number. The node can influence by knowing many nodes or the node can influence by knowing a few nodes.

Second, we evaluated the closeness centrality. The closeness centrality is defined that how close on average, the node are from itself to others. Mathematically, the closeness centrality is defined as

$$\frac{N-1}{\sum_{j=1,j\neq i} d(v_i, v_j)} = \frac{1}{L_i} \tag{3}$$

where $d(v_i, v_j)$ is the a distance between nodes v_i and v_j. L_i is the an average distance from node v_i to other nodes.

The betweenness centrality is the degree to bridge and control the flow of information in a network for the nodes. Mathematically, betweenness centrality is defined as

$$b_i = \frac{\sum_{i_s=1,i_s\neq i}^{N} \sum_{i_t=1,i_t\neq i}^{i_s-1} \frac{g_i{}^{(i_s,i_t)}}{N_{i_s,i_t}}}{(N-1)(N-2)/2} \tag{4}$$

where ${g_i}^{(i_s,i_t)}$ is the number of vertices in the shortest path going from the start point v_{i_s} to the end point v_{i_t}. N_{i_s,i_t} is the number of shortest paths from the start point to the end point.

3. Results and Discussion

This study considered the acquired period (2003-2022), three periods with ten years as one term. The first period was 2003-2012, the second was 2008-2017, and the third was 2013-2022. Table 1 shows the network indicators (number of nodes, number of edges, cluster coefficient at the largest community in the network, average degree in the network and the shortest path in the largest community in the network) for each of the three periods.

Table 1: Network properties for 3 periods. The first period was 2003-2012, the second was 2008-2017, and the third was 2013-2022, respectively, where CC indicates the cluster coefficient of largest cluster in the network.

	1st period	2nd period	3rd period
# of nodes	300	529	443
# of edges	333	633	495
cc	0.227	0.231	0.233
ave of degs	2.22	2.39	2.23
shortest path	4.89	5.12	5.69

From Table 1, we find three things:

1. The average order increases with time.
2. The average path length also increases with time.
3. In all cases, the cluster coefficients are significant and monotonically increasing.

From this, we can see that the network is becoming more and more complex as time series changes and that leading firms are emerging. Our results suggest that the network may access information through "hub" firms.

We can get the same results from the graph network we draw for the co-application network, as shown in Figure 1.

Next, we discuss network characteristics in terms of three centralities (the between centralities, the eigenvector centralities, and the closeness centralities). The between centralities can be regarded as the amount of information passing through the network, while the eigenvector centralities can be

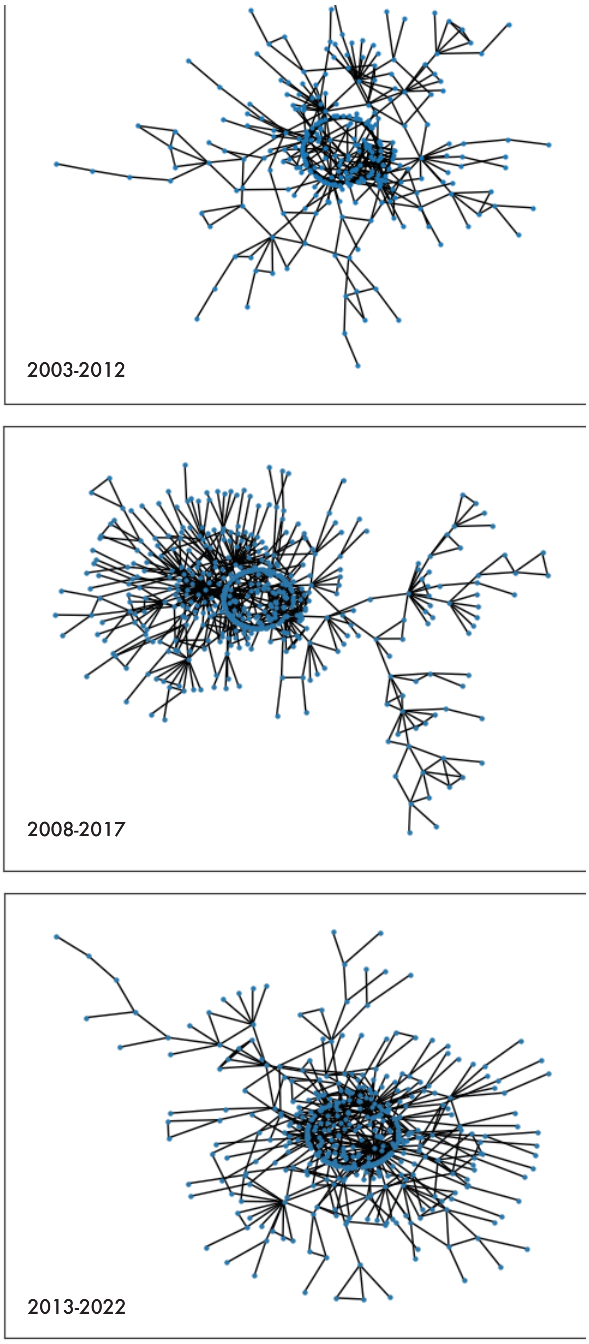

Figure 1: the co-application graph at the largest community in the network.

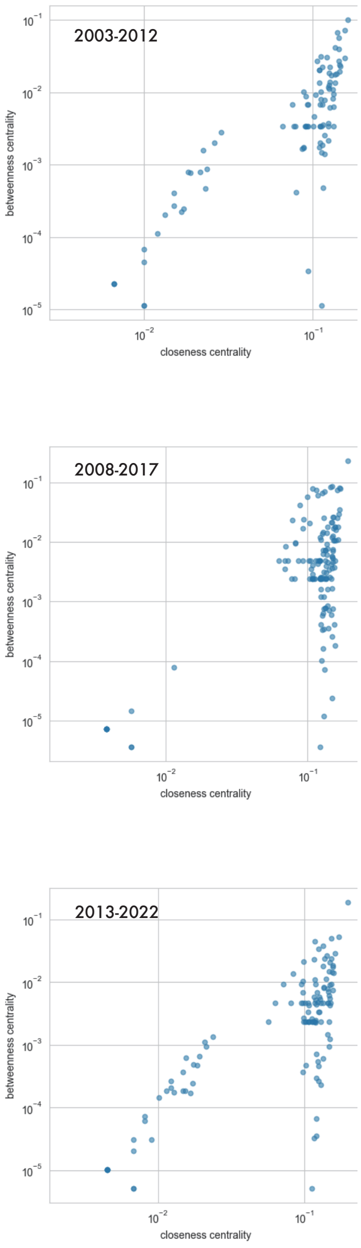

Figure 2: the dependency for the closeness centralities and the between centralities.

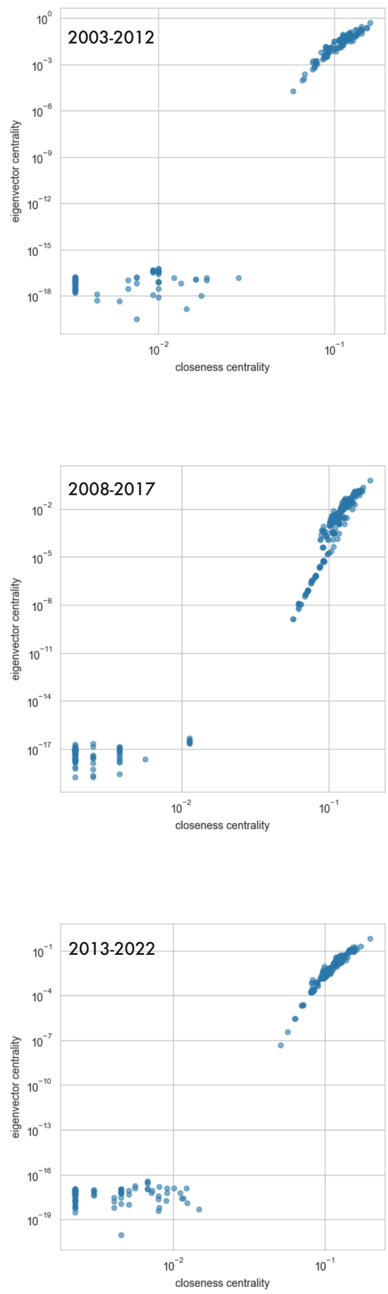

Figure 3: the dependency for the closeness centralities and the between centralities.

regarded as the importance or influence in the network. The closeness centralities refer to the closeness to other nodes.

Figure 2 and 3 show the dependency between the closeness centralities and the between centralities, and the closeness centralities and the eigenvector centralities. In both figures, we see a division into two parts. That is, there are elements in the network that are less influential and have a small amount of information passing through them, while there is a clear division between elements that are more influential and have a large amount of information passing through them. This division of roles becomes even more evident as the network matures. In other words, the clarification of the roles of each element in the network develops as the network grows.

4. summary

This paper analyzes the temporal evolution of R&D networks by conducting a time-series network analysis of joint application patents for lithium rechargeable batteries. As a result, we were able to observe the network structure in the budding, developing, and mature stages of R&D. We were also able to analyze the roles of each node in each network. We prefer to conduct a more dynamic social network analysis to obtain more detailed results.

However, so far, knowledge exchange and innovation at the cluster level have been prevailing analysed in cross-sectional terms and not in longitudinal terms. Most of the studies rely on a group of relatively simple network measures. Measures typically used have been employed to compare knowledge networks in the industrial fields, then linking networking with the innovativeness at the firm and the cluster levels. The potential of the social network analysis(SNA) seems to be outstanding and the application of more advanced dynamic SNA tools and measures could play a key role in advancing our knowledge on innovation networks.

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