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Effects of knowledge diffusion on international joint research and science convergence: Multiple case studies in the fields of lithium-ion battery, fuel cell and wind power

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ABSTRACT

The goal of this study is to investigate relationships among IJR (international joint research) network, knowledge diffusion and science convergence. Based on scientometric analysis, lithium-ion battery, fuel cell and wind power were evaluated by regression analysis statistically. The following three hypotheses were established and verified: countries having higher centrality in IJR networks are more likely to be early adopters; knowledge diffusion increases as IJR network density increases; and science convergence increases as knowledge diffusion increases. For verifying hypotheses, we measured annual number of countries as knowledge diffusion, annual Rao–Stirling index as science convergence and annual network density, degree centrality of IJR network and conduct regression analysis among these. In conclusion, an important implication is that knowledge diffusion may significantly contribute to increase science convergence and international joint research network, one of the major sources of innovative technologies.

1. Introduction

In recent innovation trend, emerging sectors are characterized by rapid development of technologies based on combining various fields and increased necessity of interdisciplinary research, which is called convergence (Xing et al., 2011).

Definition's difference between convergence and fusion is defined by Curran et al. By that definition, convergence is defined as the process where the science, technology, and industry move to the different branches and are combined. And fusion is defined as the process where two technologies are combined at least in one branch.

Convergence has attracted growing interest among many researchers (Curran, 2010; Pennings and Puranam, 2001; Stieglitz, 2003). So far, the emerging discussion on convergence has tended to focus on developments within the information technology, communications and media industries (Yoffie, 1997; Lei, 2000). Most of the studies around convergence have centered on topologies, consequences and drivers.

Convergence is separated by science convergence, technological convergence, market convergence and industry convergence, it has a mutual continuity. This study was performed around the science convergence in which the convergence starts. While knowledge diffusion is one of the most important drivers of science convergence, various factors, including changing market environments and customer behavior, regulation absolutely. Also, knowledge diffusion is affected by International Joint Research (IJR) network in terms of researcher level and network level.

Despite the fact that knowledge diffusion seems to be a major driver of science convergence and it is affected by IJR network, these phenomena remain largely unexplored in the academic field. Although a number of prior studies on science convergence, knowledge diffusion and IJR network can be identified, the academic discussion on relationships among these factors so far must be considered as still emerging, meaning that the topic remains relatively uncharted empirically (Pennings and Puranam, 2001; Stieglitz, 2003; Lind, 2005).

The purpose of the proposed this study is to investigate relationships between these factors and monitor trend of science convergence, through in-depth case studies. The overall objective of this study is thus to further the knowledge of how IJR network affects knowledge diffusion and how knowledge diffusion affects science convergence.

For monitoring science convergence and investigating relationship among these factors, we establish analytical framework and conduct case studies of lithium ion battery, fuel cell and wind power using academic paper information. Lithium ion batteries, fuel cell and wind power are being widely regarded as one of the near-term solution to deal with the variations of renewable energy sources. Lithium ion batteries have gained a lot of attention since their superior energy density and cycle life compared to other battery systems. These benefits have made lithium ion batteries almost ideal for usage in eco-friendly vehicle and energy storage systems (Wagner et al., 2013). According to

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emerging energy storage and eco-friendly vehicle, lithium-ion battery, fuel cell and wind power are representative fields that have occurring convergence among electrochemical, materials, IT and energy and so on. Therefore they are suitable fields to figure out the phenomenon of convergence.

As network analysis is able to analyze the degree of IJR quantitatively, network analysis is utilized to measure a degree of IJR network such as degree of centrality and network density.

In case of knowledge diffusion, it was defined as increasing number of participating countries and measure annual participation of countries, VOSviewer program which is developed by Leiden University and Rao–Stirling index discussed in interdisciplinary research are used.

The contributions to current knowledge that proposed that this study should provide are twofold. Firstly, an analytical framework for analyzing science convergence will be developed and applied and tested on industry currently affected by science convergence. With the aim of advancing and enriching the literature on IJR network, knowledge diffusion and science convergence, this framework will investigate relationships among these factors. Secondly, both the response and the strategic options of countries affected by science convergence, with a specific focus on the capability gap are caused by science convergence. This should shed light on how to facilitate science convergence.

Academic paper	Information of organization	Information of Nationality
Paper 1	Organization 1; Organization 2	Country 1; Country 2
Paper 2	Organization 1; Organization 3	Country 2; Country 3
Paper 3	Organization 2; Organization 4	Country 1; Country 4
Paper 4	Organization 2; Organization 3	Country 1; Country 3
…	…	…

Making Co-occurence

	Country 1	Country 2	Country 3	Country 4
Country 1	3	1	1	1
Country 2	1	2	1	0
Country 3	1	1	2	0
Country 4	1	0	0	1

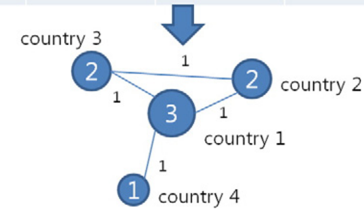

Fig. 2. An example of method of creating an IJR network diagram (example).

2. Literature review and research model

The existing literature on relationship among IJR network, knowledge diffusion and science convergence can roughly be divided into: 1) studying relationship between IJR network and knowledge diffusion; and 2) studying knowledge diffusion as driving factor of science convergence.

2.1. International Joint Research network and knowledge diffusion

International Joint Research network has always been implied, often without elaboration, in the knowledge diffusion literature: knowledge diffusion through a social system has usually been studied as a process of communication between connected researchers (Rogers, 2003; Iacobucci, 1996). Knowledge diffusion researchers employing the IJR network perspective have sought to explicate the actual structure of relationships that shape and constrain the communication, thus throwing further light on the knowledge diffusion process. The core idea in IJR network tradition is that social structure influences the spread of new ideas and practices by shaping patterns of interaction within IJR network (Burt, 1987). The fundamental intuition of IJR network theory of knowledge diffusion is that structural patterns determine whom given researchers will choose as a "model". While IJR networks are composed of relationships between a set of researchers, there are two broad approaches to the study of how relationships influence knowledge diffusion: relational and structural models of knowledge diffusion (Valente, 1995). Relational models consider the focal researcher's adoption or non-adoption in light of the behavior of those to whom the former is directly connected. Thus, for a given researcher, direct contact with an influential "opinion leader" might be seen as impelling adoption. Structural models, in contrast, consider all relationships in IJR network, rather than only the direct ties that a given researcher may have. Founded on the key assumptions of IJR network analysis (Wellman, 1988), structural IJR network models acknowledge that the overall structure of the IJR network, as well as a given researcher's position in it, influence that researcher's behavior and subsequent performance. In modeling the effect of the overall IJR network structure on knowledge diffusion, we adhere to the structural model. The history of IJR network model of knowledge diffusion may be traced (Valente, 1995) from opinion leadership formulations (Coleman et al., 1966), to the strength of weak ties formulation (Granovetter, 1973), to the communication IJR network formulation (Rogers and Kincaid, 1981) and finally to the structural equivalence formulation. IJR network analysts refer to the specific process of knowledge diffusion; thus, the chief concern of IJR network model of knowledge diffusion is the variety of network mechanisms through which knowledge diffusion operates (Burt, 1987). In this study, we draw upon and expand the core ideas in this literature. The following key conclusions of the existing IJR network research on

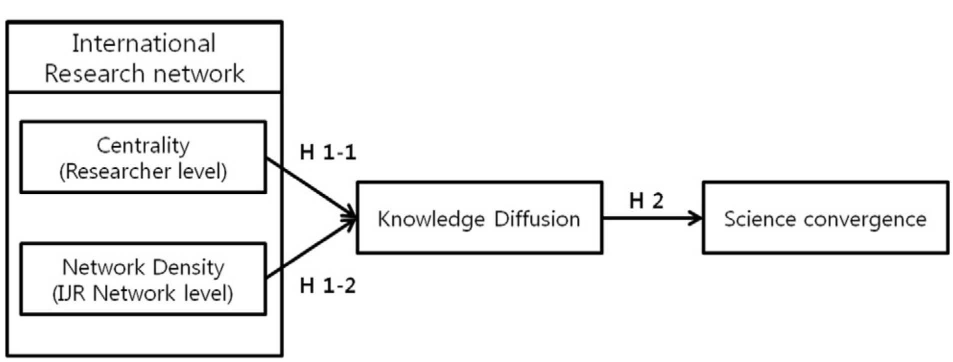

Fig. 1. Analytical framework.

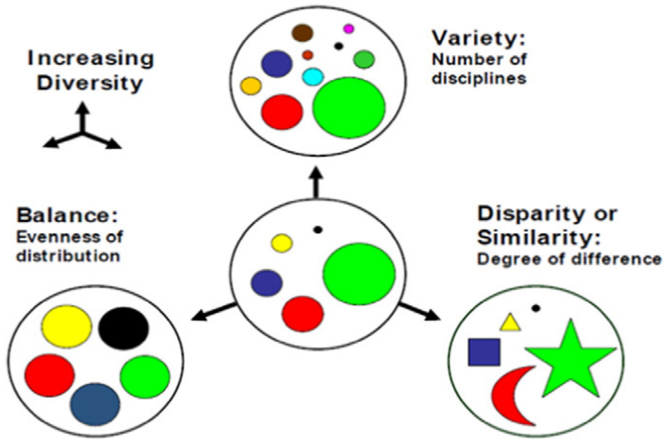

Fig. 3. Schematic representation of the attributes of diversity, based on Rao–Stirling.

the knowledge diffusion serve as background to our model development. These nine conclusions have been clustered into actor-level and network-level groups, depending on the relevant unit of analysis.

In the Researcher level (with primary reference to the position of researcher in the IJR network), firstly, knowledge diffusion is positively associated with the researcher's prominence in the IJR network (a crude measure of which is the number of a researcher's contacts), which may be viewed as indicative of opinion leadership (Rogers, 2003) or, in a related manner, as a measure of how well integrated the researcher is (Coleman et al., 1966). Secondly, highly central researchers are more likely to be early adopters (Coleman et al., 1966; Becker, 1970; Burkhardt and Brass, 1990; Madhavan et al., 1998). Potential adopters who are highly central tend to have higher reputations that they are less willing to risk by adopting unproven or contra-normative innovations; peripheral players have less at stake and may be more willing to take such risks (Rogers, 2003; Abrahamson and Rosenkopf, 1997).Thirdly, isolates, i.e. researchers who are not connected to anybody else, tend to show considerably later adoption times (Rogers and Kincaid, 1981). Fourthly, weak ties, i.e. researchers that serve as bridges between unconnected groups, are important links in the knowledge diffusion process (Burt, 1987; Granovetter, 1973). Lastly, knowledge diffusion is positively associated with structural centrality, i.e. how significant a position the researcher has in the network. For example, betweenness centrality measures the degree to which a searcher lies between other researchers (corresponding to potential control), while closeness centrality measures the degree to which a researcher is close to others (corresponding to potential access). Researchers who are highly central in these respects are more likely to receive related information and influence early, and hence more likely to adopt early (Burkhardt and Brass, 1990).

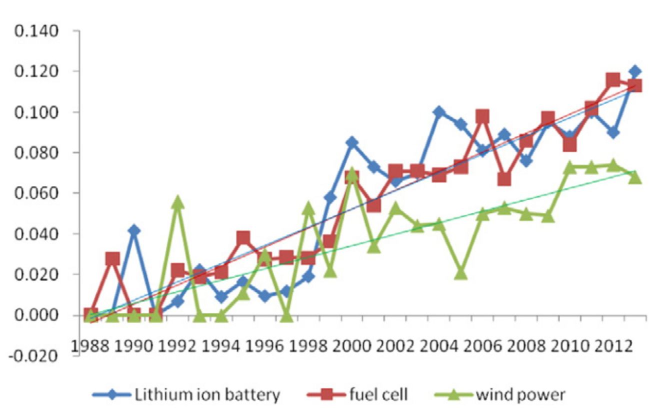

Fig. 4. Annual IJR network density.

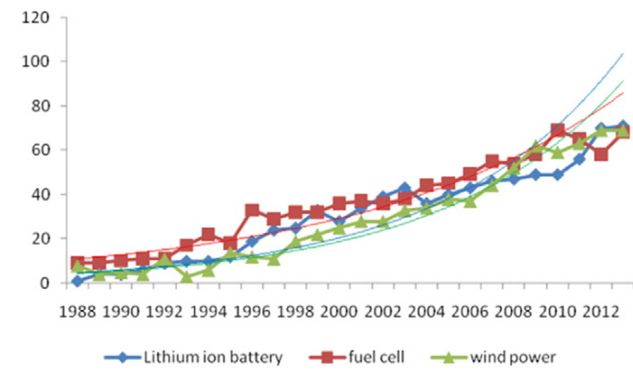

Fig. 5. Annual number of participating country.

In IJR network-level (with primary reference to overall patterns of relationships), mainly, highly centralized IJR networks (with a small number of highly central researchers) should demonstrate a higher rate of knowledge diffusion; once adopted by the central researchers, the knowledge diffusion will spread rapidly through the IJR network (Valente, 1995). Secondly, knowledge diffusion will be more rapid in IJR networks that are densely interconnected (Black, 1966). Thirdly, knowledge diffusion operates through cohesive ties, i.e. through strong connections with close contacts (Coleman et al., 1966). Lastly, an alternative hypothesis to knowledge diffusion through cohesion is that it operates through structural equivalence, i.e. researchers may take their cues from others that they consider to be similar to themselves, even in the absence of direct ties between them (Burt, 1987). Against the background provided by the current IJR network literature on the knowledge diffusion, we establish hypothesis like:

H 1-1. in the Researcher level: Countries having higher centrality in IJR networks are more likely to be early adopters.

H 1-2. in IJR network-level: Knowledge diffusion increases as IJR network density increases.

2.2. Knowledge diffusion as driving factor of science convergence

The underlying causes and drivers of science convergence are diverse. A first set of causes has been identified in changing market environments and customer behavior. The phenomenon of one stop shopping, i.e. customers seeking the full of multiple needs within only one transaction, leads to a convergence of formerly distinct markets (Lind, 2005). A second set of causes for science convergence comprises political, legal and regulatory aspects which encompass regulation as well as deregulation, standardization, legislature, government funding and the way governmental authorities deal with debated issues

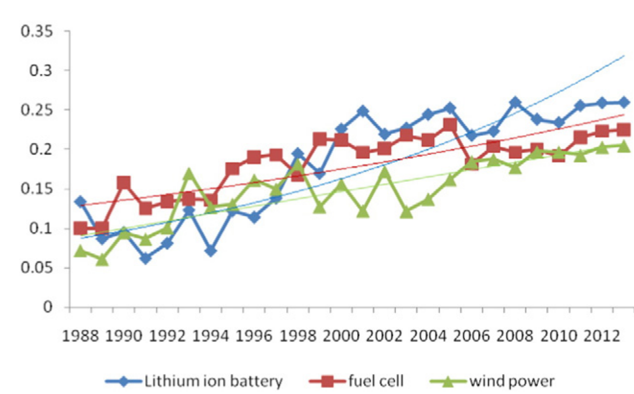

Fig. 6. Annual Rao–Stirling index.

Fig. 7. The network diagram of IJR: lithium ion battery (1988–1998).

(Yoffie, 1997; Bally, 2005; Choi and Valikangas, 2001; Choi et al., 2007; Nystroem, 2007; Nystroem, 2008). As the example of the NFF sector shows, it is especially regulation that plays an essential role in regard to the question whether Functional Foods will compete with conventional foods and/or pharmaceutical industry drugs in the future (Bröring, 2005). In the ICT sector, the role of regulation in the process of science convergence is also subject of an interesting discussion. On the one hand, regulation is considered a mere barrier to science

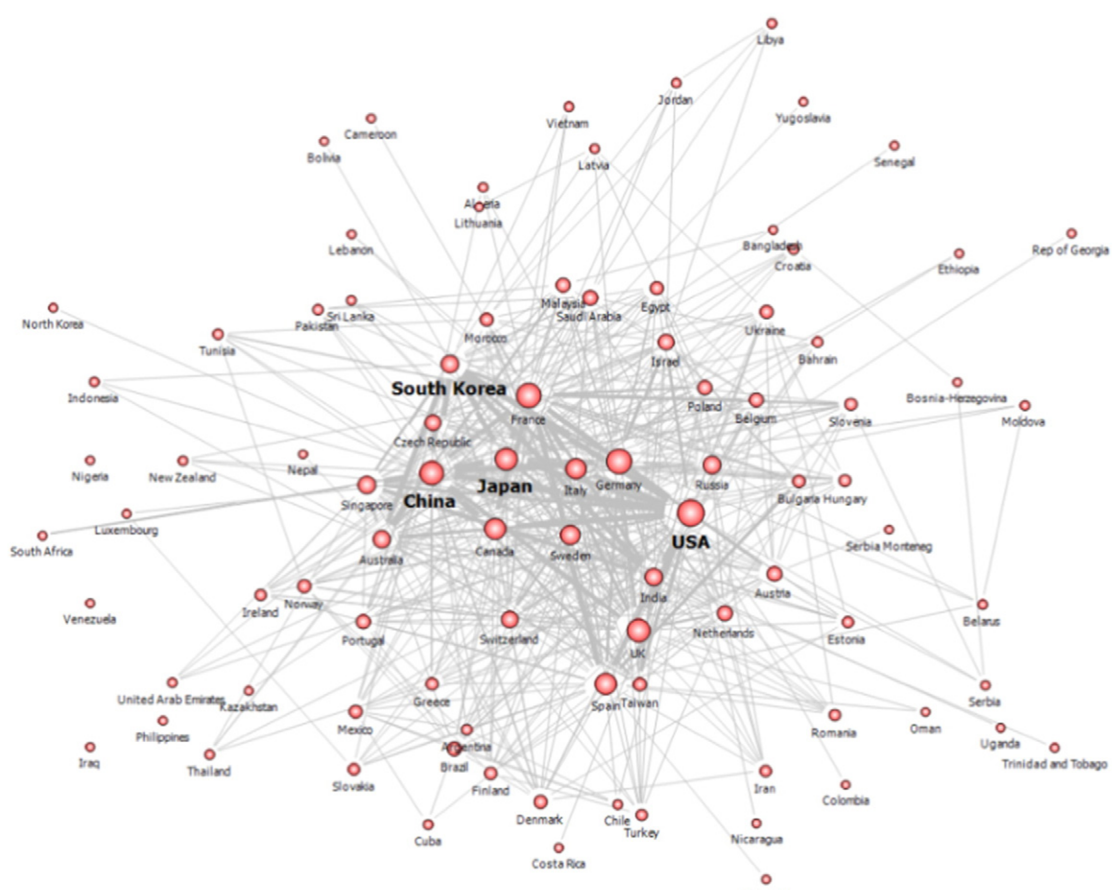

Fig. 8. The network diagram of IJR: lithium ion battery (1999–2013).

Fig. 9. The network diagram of IJR: fuel cell (1988–1999).

convergence due to the mono-poligopolization of the telecommunication sector in the past (Katz, 1996). On the other hand, it is also regarded as an important driver for science convergence in this area. For instance, Nystroem (2007, 2008) concludes that regulation may also aim at fostering science convergence developments, e.g. in regard to internet services or multi-purpose devices. Deregulation of a given industry is often a result of policy makers' desire to induce competition by lowering entry barriers for new competitors that bring alternative technologies or business models into an industry (Lei, 2000; Bores et al., 2003). Deregulation has predominantly been a driving factor in the telecom industry (Katz, 1996) leading to convergence such as that between data communications and traditional fixed telephony, i.e. 'Voice over IP' (Nystroem and Hacklin, 2005; Curwen, 2006). The next area ripe for deregulation would likely be the mobile telephony sector (Vong and Finger, 2006). A third set of science convergence cause, which has attracted most interest in literature on science convergence so far, is knowledge diffusion (Bierly and Chakrabarti, 1999). Knowledge diffusion is undoubtedly the principal driver behind science convergence that is discussed in existing literature. Knowledge diffusion is integral in many cases of science convergence, and thus also central as a driver for science convergence (Nystroem and Hacklin, 2005).This holds especially true for science and technologies intense industries like the ICT sector (Lind, 2005; Katz, 1996; Nystroem and Hacklin, 2005).

Against the background provided by the current driver factor literature on the science convergence, we establish hypothesis like that:

H2. Science convergence increases as knowledge diffusion increases.

In this study, we establish analytical framework of relationship among IJR network, knowledge diffusion and science convergence based on previous study and verify it through regression analysis (Fig. 1).

3. Methodology

3.1. Extraction of academic paper and making IJR network

We extracted 20,008, 20,359 and 6324 cases of academic papers published from 1988 until 2013 in the fields of lithium ion battery and fuel cell from the Web of Science (WoS) database using the related keyword information (Table 1). In the search query, either TS or TI in each field to increasing accuracy of data is used. This dataset was used for hypothesis testing SCOPUS and GOOGLE, WoS offers simultaneous access to Science Citation Index Expanded (SCIE), Social Science Citation Index (SSCI) and Art & Humanities Citation Index (AHCI) and enables us to analyze academic papers of higher caliber since they only offer information on the academic papers of SCIE class or higher from around the world. The used keywords were major keywords to represent its fields. In extracted dataset, organization data and their nationality data are used for making IJR network. In analysis of IJR network, we divided into two periods following high and low IJR density.

Table 1
Search query.

	Search query	No. of Cases Searched
Secondary battery	TS: (secondary* or rechargeable* or lithium ion) and battery* and article and span time: 19880101–20131231	20,008
Fuel cell	TI: fuel and cell* and article and span time: 19880101–20131231	20,359
Wind power	TI: wind adj (power* or turbine* or generator*) and article and span time: 19880101-20131231	6,324

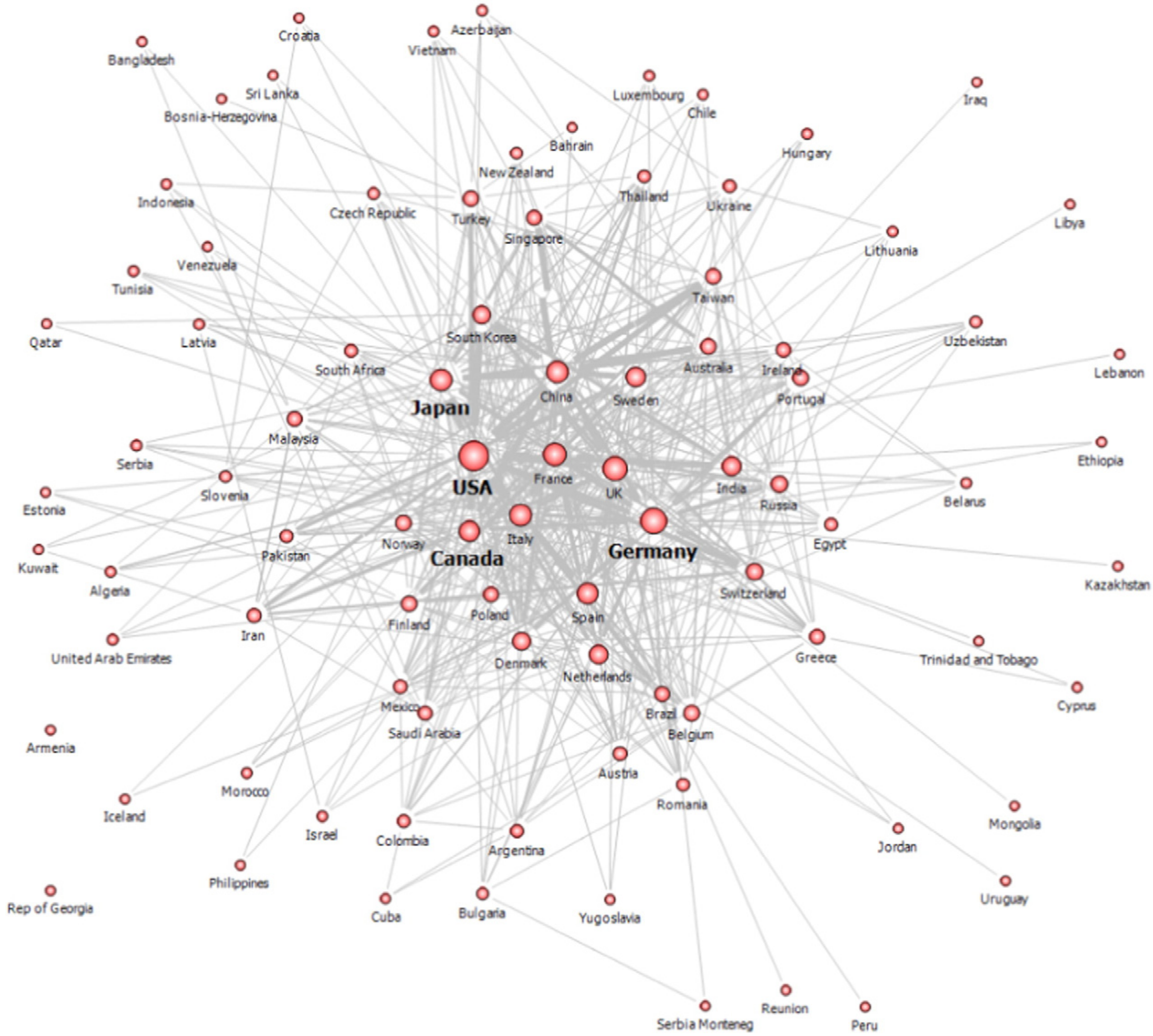

Fig. 10. The network diagram of IJR: fuel cell (2000–2013).

A diagram of IJR networks was drawn by creating a simultaneous occurrence matrix table using the paper information, extracting the country information of the organizations involved in joint research and creating a diagram based on the resulting information, as shown in Fig. 2. (See Fig. 3.)

3.2. Measurement of IJR network

To measure an interconnection of IJR network and who play a role as network hub in IJR network, both network density and degree centrality were analyzed. Network density is expressed as the ratio of the number of the lines indicated in the diagram to the number of all the connectable lines, and is calculated from the following formula:

$$\text{Network density} = \frac{L}{\frac{n(n-1)}{2}} \tag{2}$$

Here, L is the number of existing lines and n is the number of nodes in the network. In this formula, the denominator, $n(n-1)/2$, is the maximum number of connectable lines in the network. The network density ranges from 0 to 1. For example, a network density 0 has no connections and a network with density 1 has all the nodes connected. In this study, nodes represented countries and lines represented the number of IJR cases. Therefore, if IJR exists between two countries, they are connected with a line, but if not, they are not connected.

The degree of centrality in the connection between the participant countries in IJR network structure is measured using the following formula:

$$\text{Degree of Centrality} = \frac{p_i \cdot p_k}{n(n-1)} \tag{3}$$

The value of $p_i \cdot p_k$ is defined as 1 when i and k are connected in the network, and 0 if not connected.

3.3. Measurement of knowledge diffusion

The main elements of knowledge diffusion are communication channel, time and increasing number of adopter through interaction between the members of the social system. Considering these elements, we define knowledge diffusion as like this: knowledge diffusion is the process of increasing the number of adopters that participate in studying through channel of communication between adopter and non-adopter. As a definition of knowledge diffusion, we measured knowledge diffusion by number of participating countries.

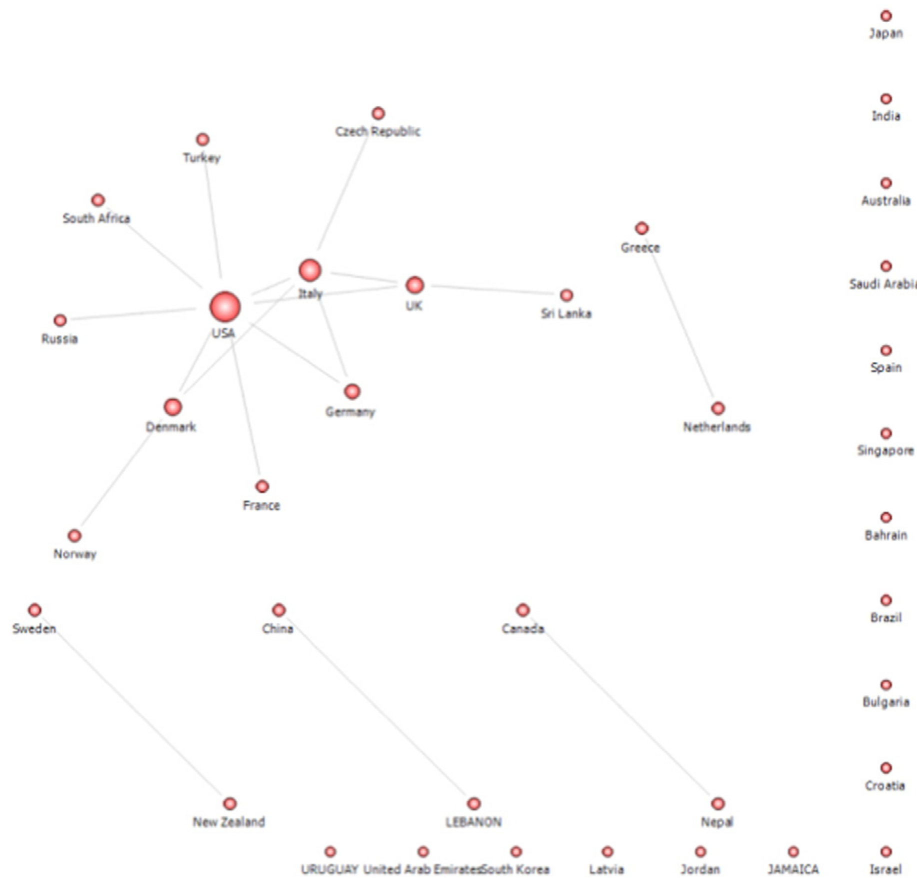

Fig. 11. International joint research networks in wind power field (1988–1999).

3.4. Measurement of science convergence

Annual science convergence in the lithium ion battery, fuel cell and wind power was measured using the Rao–Stirling index discussed in the interdisciplinary studies, which is defined as the study that integrates different knowledge, including conceptual, theoretical and information knowledge (Academies, 2005). Fig. 4 illustrates interdisciplinary studies in terms of variety, balance, and disparity (Rafols and Meyer, 2010), which are the number of different categories, the degree of category distribution and the degree of difference among categories respectively (Purvis and Hector, 2000). Since convergence means a combination of two or more science, technology or industry, as noted in the definition of existing convergence, it is deemed very useful to use a Rao–Stirling index of interdisciplinary studies as the convergence index. Therefore, in this study, we determined the increasing in science convergence with the increasing in Rao–Stirling in which all three aspects were applied and it is measured using the following formula (Stirling, 2007):

$$\text{Rao}-\text{stirling Index} = \sum_{ij} d_{ij} p_i p_j \tag{4}$$

Here, d_{ij} represents distance between i and j using cosine coefficient and p_{ii} and p_{jj} each represents the ratio of occurrences in population (Fig. 2).

VOSviewer is a freely available computer program that Eck and Waltman have developed for constructing and viewing bibliometric maps. Unlike most computer programs that are used for bibliometric mapping, it pays special attention to the graphical representation of bibliometric maps. Also, the functionality of VOSviewer is especially useful for displaying large bibliometric maps in an easy-to-interpret way and it is mainly used in creating a map based on network data (Eck and Waltman, 2010). This is done in three steps. The first step is the calculation of association among categories based on the simultaneous occurrence matrix table. Association is calculated with the association strength method using the following formula:

$$\text{Association strength (aij)} = \frac{mC_{ij}}{C_{ii}C_{jj}} \tag{4}$$

Here, Cij represents the number of occurrences between i and j, and Cii and Cjj each represents the number of occurrences involving i and j, respectively. Also, m presents the number of population. In the second step, a two-dimensional map is drawn based on the association calculated in the first step. The relationship with higher association is represented by positions with a closer distance and the relationship with lower association is represented by positions with a further distance. The final step is the clustering of variables and the indication of the density of the variable according to their frequency of occurrence (Eck and Waltman, 2010). VOSviewer, therefore, is a program that shows the relationship among variables according to the distances among fields and enables monitoring of the science convergence trend among the fields. In monitor of convergence, we divided into two periods following high and low IJR density to investigate relationship between IJR network density and science convergence.

4. Results

4.1. Basic statistical analysis

Analysis of the IJR network density in the field of lithium ion battery, fuel cell and wind power showed a linear pattern through time (Fig. 4).

Analysis of the annual number of participating country in the lithium ion battery, fuel cell and wind power showed an exponential functional pattern through time (Fig. 5).

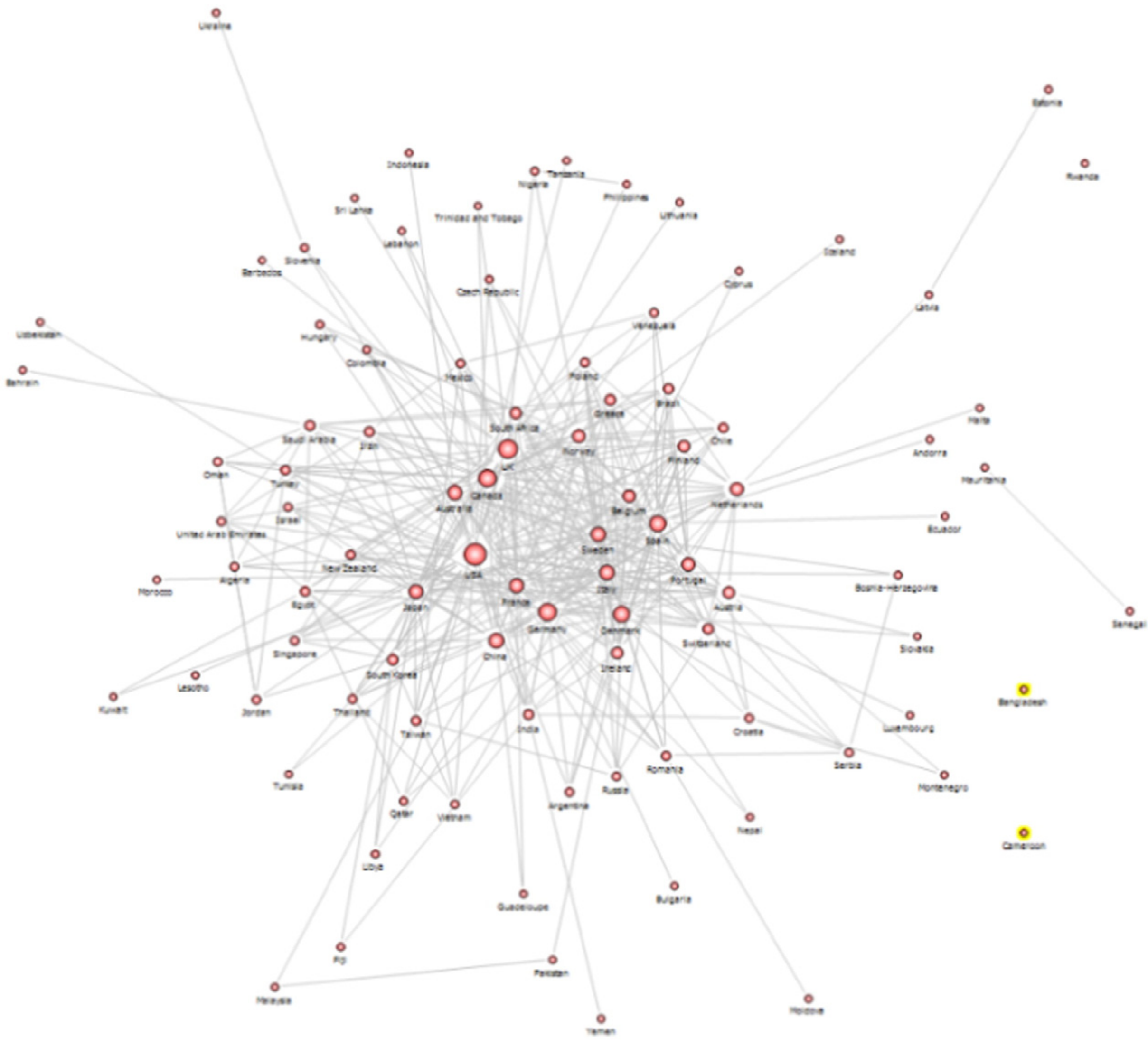

Fig. 12. International joint research networks in wind power (2000–2013).

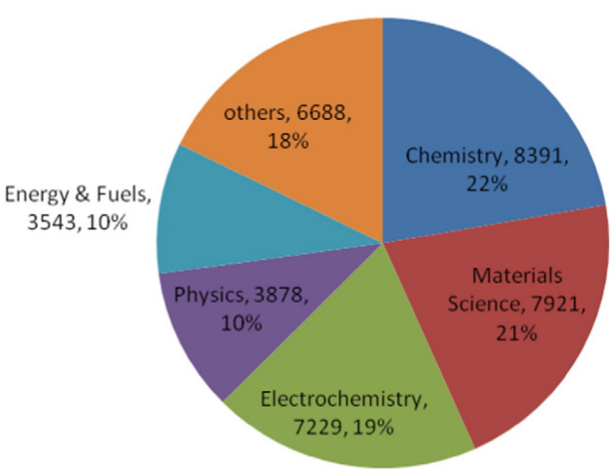

Fig. 13. Proportion of subject categories: lithium ion battery.

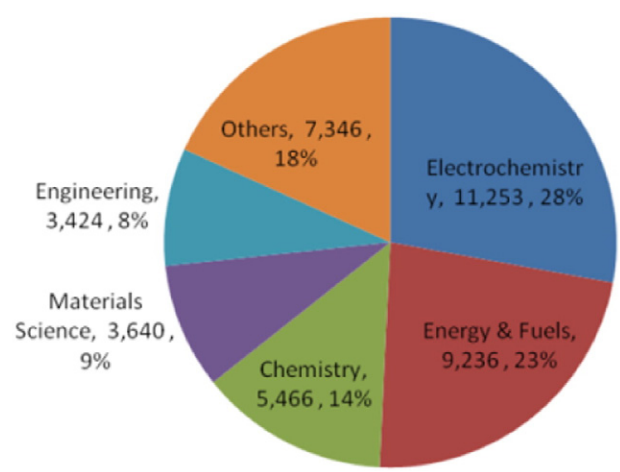

Fig. 14. Proportion of the subject categories: fuel cell.

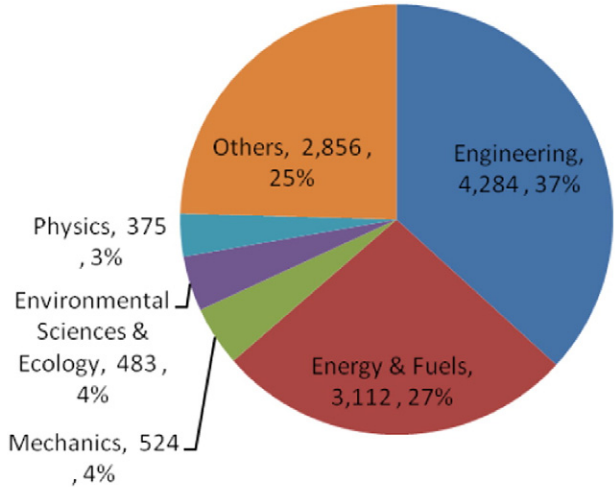

Fig. 15. Proportion of subject categories in wind power.

Analysis of the annual Rao–Stirling index showed an exponential functional increase pattern of the Rao–Stirling index in the lithium ion battery and fuel cell field. In case of wind power, Rao–Stirling index showed a linear pattern through time (Fig. 6).

A network diagram of IJR in lithium ion battery was created based on the information from the papers published from 1988 to 1998. 31 countries published papers in lithium ion battery field and 27 of 31 were involved in IJR. Especially, 8 cases of joint research were conducted by the USA and Japan (Fig. 7).

The structure of IJR networks in the lithium ion battery after 1999 revealed that 87 countries had been publishing papers through IJR. These include 418 cases of joint research by the USA and China and 232 cases by the USA and Korea, showing active IJR activities between these countries. The USA was also actively involved in IJR with Singapore and Australia (Fig. 8).

A diagram of IJR network in fuel cell was created based on the information from academic papers published from 1988 to 1999. 39 countries published academic papers in the fuel cell and 30 of 39 countries were involved in IJR. Especially, 6 cases of joint research were conducted by Canada and Belgium and 3 cases by the USA, Japan and Denmark (Fig. 9).

The structure of the IJR networks in the fuel cell after 2000 revealed that 87 countries except Armenia and Georgia have been participating in IJR. Among these, there have been 306 and 146 cases of IJR by the USA, China and Korea, respectively (Fig. 10).

A diagram of IJR networks was created based on the information from papers published from 1988 to 1998. Among these papers, 37 countries published academic papers in the wind power, of which 20 were involved in IJR. Especially, there were cases of joint research being conducted led by the USA followed by Italy, Russia, Denmark and France. However, there has been no active IJR (Fig. 11).

A diagram of IJR networks was created based on the information from academic papers published from 2000 to 2013. Among these papers, 94 countries published academic papers in the wind power field, of which 91 were involved in IJR. This means that active IJR has been conducted in the wind power field since 2000 (Fig. 12).

The proportion of subject categories during the whole period in lithium ion battery showed that studies in the fields of chemistry, material science, electrochemistry, physics and energy accounted for 82%. It was indicated that lithium ion battery was active through science convergence of these five disciplines (Fig. 13).

In case of fuel cell, the proportion of subject categories during the whole period showed that studies in the fields of electrochemistry, energy, chemistry, material science and engineering accounted for 82%, indicating that fuel cell studies were being conducted through science convergence of these disciplines (Fig. 14).

In case of wind power, the proportion of subject categories during the whole period showed that studies in the fields of engineering, energy, mechanics, environment and physics accounted for 75%, indicating that wind power studies are being actively conducted through science convergence of these disciplines (Fig. 15).

Mapping of the main subject categories of the lithium ion battery field using VOSviewer revealed that electrochemistry, material science, chemistry and physics were the major subjects of study until 1999. However, since 2000, lithium ion battery studies have been associating with more subject categories. The gaps among subject categories also became narrower, especially among the fields of energy, chemistry and physics, and these sciences are currently converging, especially between the electrochemistry and material science fields (Figs. 16, 17).

Mapping of main subject categories of the fuel cell using VOSviewer revealed that electrochemistry, material science, chemistry and physics were the major subjects of study until 1999. However, since 2000, fuel cell has been associating with more subject categories. The gaps among subject categories also became narrower, especially among the fields of energy, chemistry and physics, and these sciences are currently converging, especially increasingly between the electrochemistry and material science fields (Figs. 18, 19).

Mapping of the main subject categories of the wind power field using VOSviewer revealed that engineering, energy and mechanics were the major subjects of study and that these disciplines were converging until 1999. The mapping of subject categories for the period from 2000 showed increased gaps among the fields of engineering, energy and mechanics, indicating that convergence of these fields of study

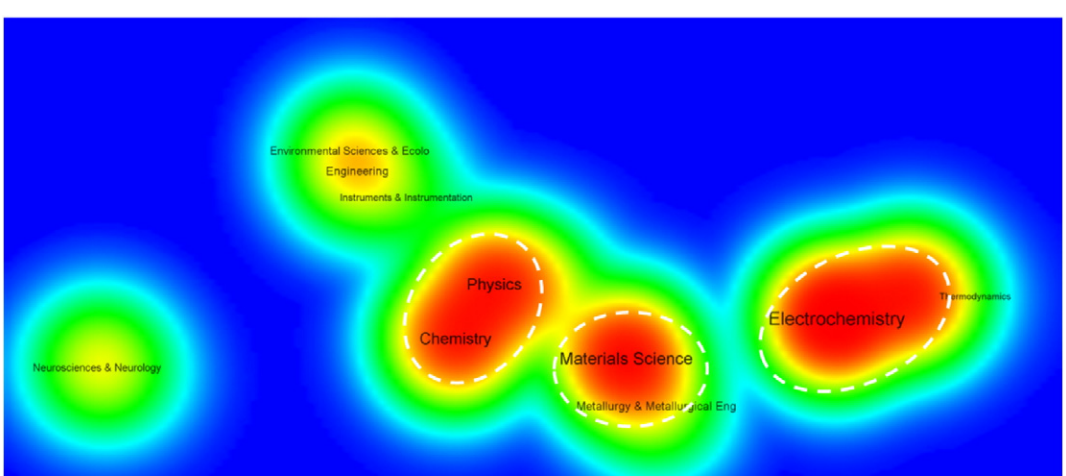

Fig. 16. Mapping of subject categories in lithium ion battery (1988–1998).

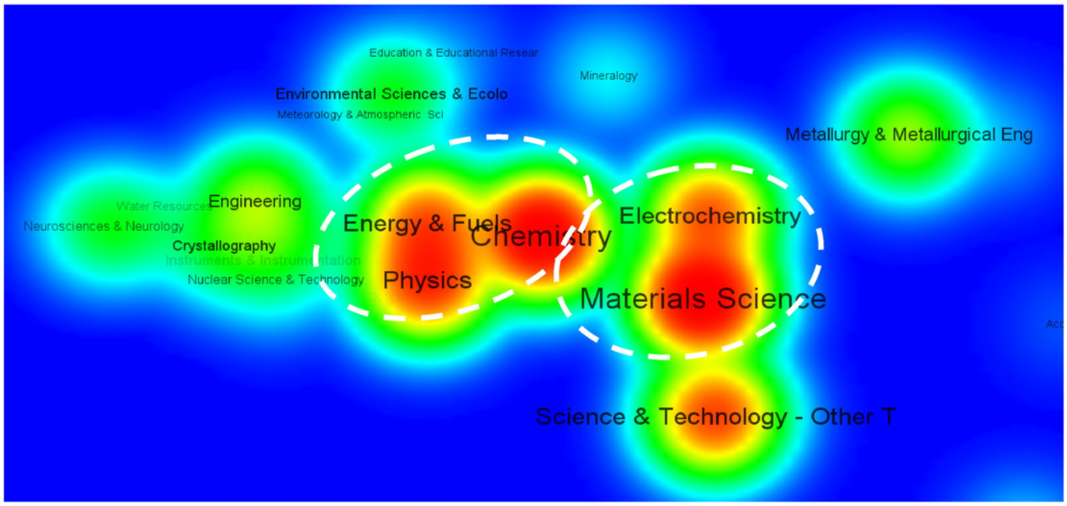

Fig. 17. Mapping of subject categories in lithium ion battery (1999–2013).

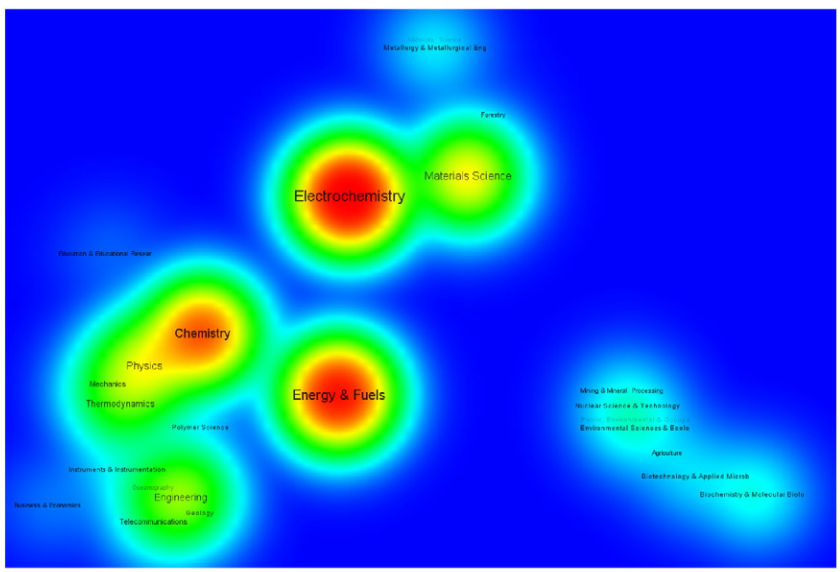

Fig. 18. Mapping of subject categories in fuel cell studies (1988–1999).

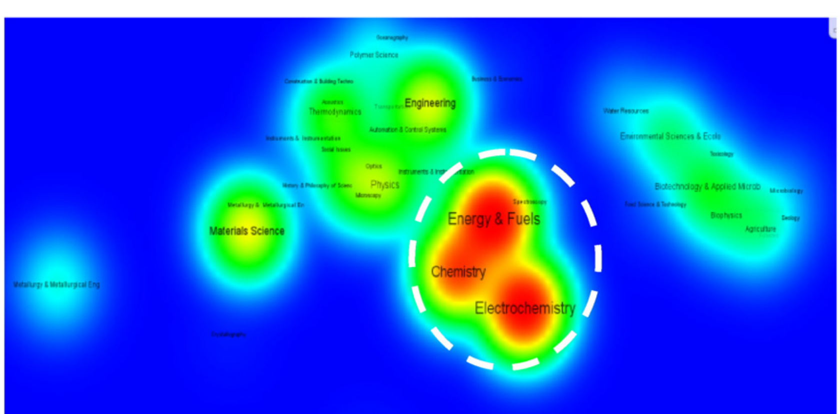

Fig. 19. Mapping of subject categories in fuel cell studies (2000–2013).

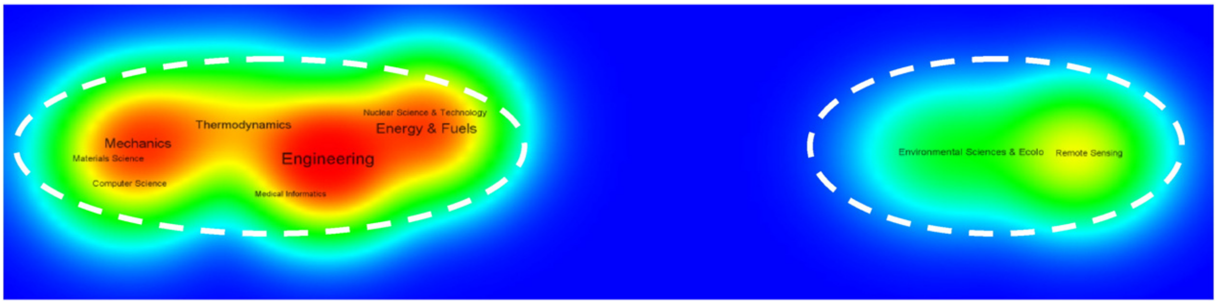

Fig. 20. Mapping of subject categories in wind power field (1988–1999).

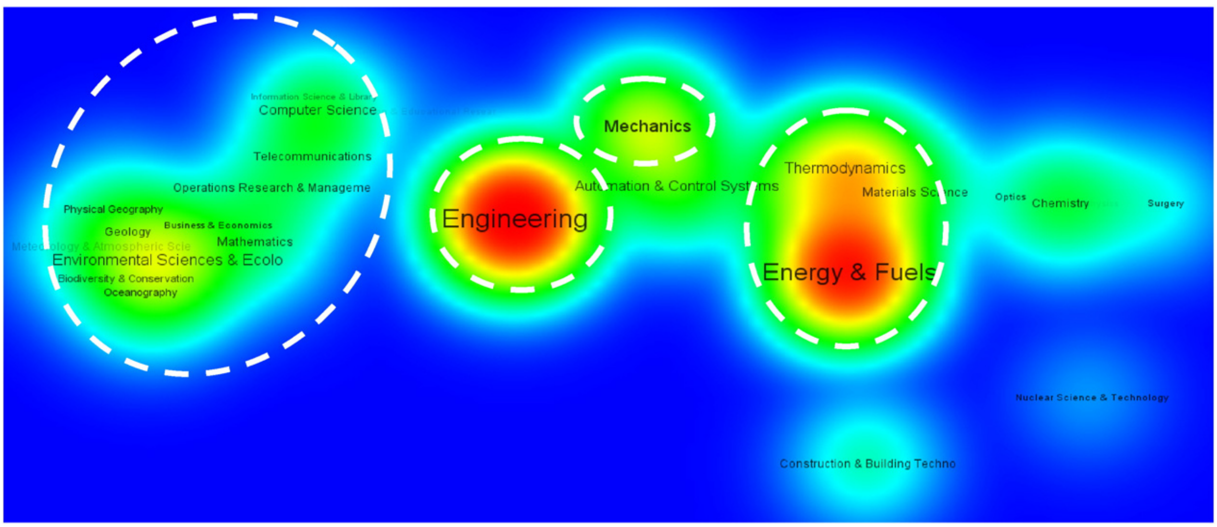

Fig. 21. Mapping of subject categories in wind power field (2000–2013).

has decreased. Instead, convergence is occurring between the field of environment, which had been an independent field of study prior to 2000, and other various fields (Figs. 20, 21).

4.2. Verification of the hypothesis H1: degree and centrality

In order to verify the hypothesis that countries with higher centrality in IJR networks are more likely to be early adopters in the field concerned, we examined the order of the centrality of connection strength and the year of first participation by the top 15 countries in IJR networks in the lithium ion battery, fuel cell and wind power. The results revealed that the USA and European countries had higher centrality of connection strength, indicating that they are playing a central role in IJR network. We also analyzed the first year of participation by the top 15 countries with high centrality of connection strength in each field: the average first year of participation was 1991 in the fields of lithium ion battery and wind power and 1990 in the fuel cell (Table 2).

Table 2
The order of the centrality of connection strength of the countries in IJR networks and their first year of participation in each field.

Field	Lithium ion battery			Fuel Cell			Wind power		
Order	Countries	Degree centrality	Year of participation	Countries	Degree centrality	Year of participation	Countries	Degree centrality	Year of participation
1	USA	0.505	1989	USA	0.636	1988	USA	0.5	1988
2	France	0.459	1989	Germany	0.509	1988	UK	0.42	1988
3	Germany	0.431	1993	UK	0.409	1988	Germany	0.37	1992
4	China	0.431	1989	Italy	0.391	1988	Canada	0.36	1988
5	UK	0.413	1992	France	0.382	1989	Denmark	0.34	1988
6	Japan	0.367	1988	Japan	0.364	1988	Spain	0.32	1988
7	Canada	0.349	1991	China	0.355	1996	Italy	0.31	1992
8	Spain	0.321	1994	Canada	0.345	1988	France	0.29	1988
9	Italy	0.321	1990	Spain	0.336	1994	Australia	0.28	1990
10	Sweden	0.303	1993	Netherlands	0.291	1988	China	0.28	1992
11	Korea	0.284	1994	Sweden	0.291	1988	Sweden	0.27	1995
12	Australia	0.266	1991	India	0.264	1989	China	0.24	1989
13	Russia	0.257	1991	Korea	0.264	1994	Norway	0.22	1995
14	Singapore	0.248	1998	Russia	0.236	1993	Portugal	0.21	2001
15	India	0.248	1992	Denmark	0.227	1991	Netherlands	0.19	1998
	Average year of participation		1991	Average year of participation		1990	Average year of participation		1991

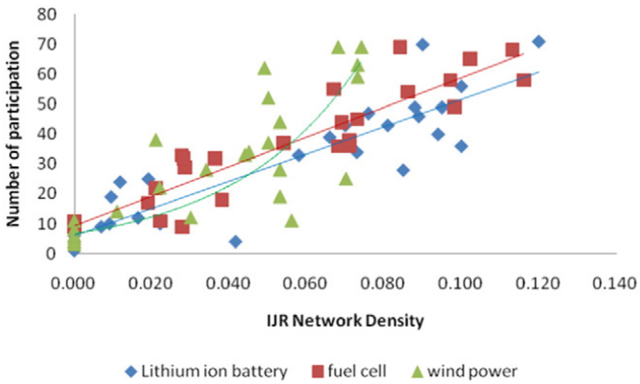

Fig. 22. Regression analysis between number of participant countries and network density: lithium ion battery, fuel cell and wind power.

4.3. Verification of the hypothesis H2: IJR network density and knowledge diffusion

The results of the regression analysis between the IJR network density and the number of participant countries in the field of lithium ion battery and fuel cell showed a linear relationship between the number of participant countries and IJR network density. In case of wind power, it showed exponential functional relationship. This means that hypothesis between IJR network density and knowledge diffusion was adopted (Fig. 22).

4.4. Verification of the hypothesis H3: knowledge diffusion and science convergence

The results of the regression analysis between the number of participant countries and the Rao–Stirling index in the lithium ion battery showed a linear relation between the number of participant countries and the Rao–Stirling index. Also, fuel cell and wind power showed exponential relation. Therefore, the hypothesis that science convergence increases as knowledge diffusion increases was adopted (Fig. 23).

5. Discussion

As the result of investigating relationships among IJR network, knowledge diffusion and science convergence, we draw some implications.

Firstly, IJR is a system of communications to diffuse knowledge. In similar, a researcher in each country is able to utilize these results in other country. Knowledge is highly portable and researchers are seeking the reward of recognition: the network may change the physical location where knowledge is created, and where it is exploited.

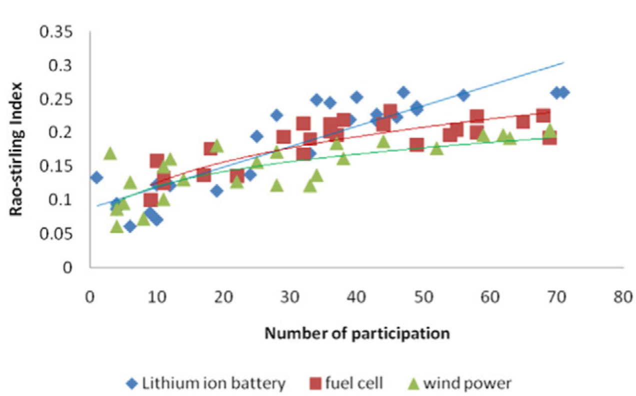

Fig. 23. Regression analysis between the number of participant countries and Rao–Stirling: lithium ion battery, fuel cell and wind power.

Secondly, once a linkage is made and research is underway, the knowledge created and shared becomes a catalyst for other links. At this point, ensuring that knowledge can flow freely within the research system is critical to both its diffusion and growth, and to the ability of any researcher to ensure that science is available to users at the local level. The dynamic shifts from the focus on the country as the system of innovation to a local–global nexus where research carried out locally becomes available within a global system. The national policy structure then becomes an enabler of knowledge flows and linkages among researchers.

This study suggests that knowledge diffusion defends on IJR network structure. To establish a system for collaborative research between countries will be attributed to an increase in the knowledge diffusion, science convergence finally will be expedited.

6. Conclusion

In this study, the three conclusions were drawn by constructing analytical framework, Firstly, knowledge diffusion is affected by IJR network structure. However, the effects of IJR network varied among the fields. Secondly, we confirmed that knowledge diffusion is an essential driving force for science convergence. However, the effects of knowledge diffusion on science convergence varied among the fields. Lastly, the early adopters that began studies early in IJR networks became the leaders in IJR.

These results render this study meaningful in the following ways. It offered statistical verification for how knowledge diffusion influences science convergence and how IJR network influences knowledge diffusion. In addition, case-based analysis revealed how the early adopters, who play an important role in knowledge diffusion, exert influence in IJR networks. And these results will be developed, applied and tested on industry currently affected by science convergence and we expect that this result can shed light on how to facilitate science convergence.

Nevertheless, the derived results are limited in that it was not verified whether knowledge diffusion always entails sharing of related science. In addition, differences were found among the study fields in terms of the effects of knowledge diffusion on science convergence. But, we don't explain enough this cause. Also, we don't conduct another factor to drive science convergence. i.e. customer behavior, regulatory aspects. Therefore, future studies will be necessary to analyze another factor except knowledge diffusion and to document the patterns of the effects of knowledge diffusion on science convergence.

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