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A systematic way of identifying and forecasting technological reverse salients using QFD, bibliometrics, and trend impact analysis: A carbon nanotube biosensor case

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ABSTRACT

Experts have more difficulty identifying reverse salients in R&D because of increasing technological complexity and a shortened technology lifecycle. As an alternative, we suggest a new and systematic method of identifying and forecasting reverse salients using QFD (quality function deployment), bibliometric analysis, and TIA (trend impact analysis). QFD allows users to systematically identify and prioritize reverse salients. An integration of QFD, bibliometric analysis, and TIA makes it possible to specify key performance indicators of reverse salient in order to identify the performance gap between current and market-required performance and to make a probabilistic forecast about when reverse salients will be corrected. Our method will help managers identify a top priority reverse salient, forecast its future, and thus make better R&D decisions with regard to market requirements. A carbon nanotube biosensor technology is used as an example.

1. Introduction

It is important to commercialize emerging technologies (Bhat, 2005) as these reshape industry structure and competition rules through disruptive technological innovation, creating new growth opportunities (Hung and Chu, 2006). For instance, polyimide technology reshaped traditional markets, creating new markets in various industries including film, display, secondary battery, and semiconductor (Mochizuki and Umeda, 2001). However, among emerging technologies, commercialization of some technologies has experienced greater than expected delay.

A number of previous studies have investigated key factors of such delay, focusing mainly on external factors including financing, human resources, absorptive capacity, and collaboration (Cheng, 2012; Holman et al., 2008; Jacobs et al., 2010; Linton and Walsh, 2008; Yanez et al., 2010). However, in early phases of technology development and commercialization, technological obstacles are more important than other obstacles, though non-technological factors become important in later phases (Jolly, 1997).

Despite their importance, there is no systematic method to identify and forecast such technological obstacles. Most previous studies depend on expert judgments (McNeil et al., 2007). However, the increasing technological complexity and shortened technology lifecycle have reduced the reliability of expert judgments, making identification increasingly difficult. As an alternative, bibliometric analysis of large technological data has been proposed but is not used much in R&D practice because it cannot specify obstacles in detail (Alencar et al., 2007; Porter and Detampel, 1995; Van Raan, 2005). Also, since forecasting is based on reliable identification, there has been little effort to forecast when technological obstacles are overcome.

Considering this past research, we suggest a new and systematic method to identify and prioritize key technological obstacles and to forecast when a technological obstacle is overcome in terms of performance. Above all, to clarify the concept of technological obstacles, we introduce reverse salience methodology. A reverse salient (RS) is defined as a subsystem that hinders the full performance potential of an entire system (Dedehayir and Mäkineif, 2008). Since we focus on technological obstacles for commercialization, we define an RS as a technological obstacle that hinders the full market potential of a technology. Note that market potential can be fully exploited when various market requirements are met by technologies. Thus, in our research, operational criteria and measures of RSs are derived from key market requirements, comprising not only externally imposed criteria such as regulation, but also internal technological performance measures. However, operational measures might vary with technology and relevant market and thus can include technological architecture, performance standards, and

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other measures. Overall, an RS is useful to define, evaluate and prioritize key technological problems.

Our method consists of three phases. In the first phase, using QFD (quality function deployment), we identify, evaluate, and prioritize RSs. In the second phase, key performance indicators of top priority RSs are defined. Through bibliometric analysis of journal papers and patents, we plot past trends of key performance indicators and identify the gap between current and desired performance for commercialization. Finally, using TIA, we perform a probabilistic forecast of achievement of the RS solution and the desired performance. TIA is a forecasting technique to create a range of future values by reflecting combined effects of important future events (Agami et al., 2009).

As an illustrative example, the carbon nanotube (CNT) biosensor is selected. The CNT is an emerging technology that can be applied to various fields, including films, solar cells, and sensors (Spitalsky et al., 2010). However, its commercialization has been limited in some high-strength products and has occurred later than industrial experts expected. Also, there is no consensus on the top priority technological RS for R&D and commercialization (Endo et al., 2008). Among various CNT-based products, a CNT biosensor typically has these problems and thus is selected.

This paper proceeds as follows. In Section 2, we review previous RS studies and existing forecasting methods, positioning our approach in the context of current literature. Then, the research framework and methodology are explained. Subsequently, an empirical analysis of the CNT biosensor is provided. Finally, we end with some discussion and conclusions.

2. Literature review

2.1. Reverse salients

In contrast with a unitary view on technology systems, a systemic view perceives a technology system as consisting of multiple interactive subsystems. If a certain subsystem cannot deliver the necessary level of performance compared with other subsystems, it can hinder the advance of the entire technology system while limiting overall performance due to the continuous interaction among subsystems. A technology system cannot make advances unless the technological obstacle is solved (Hughes, 1983). An RS can be defined as such a subsystem.

Using reverse salience, previous studies have investigated the evolution of technology systems and the role of RSs. Hughes (1983) introduced the concept of RSs to analyze a direct-current electric system generator. Similarly, Murmann and Frenken (2006) decomposed an automotive technology system into technological sub-systems, including the body and engine, and identified technological RSs. Similarly, MacKenzie (1987) identified technological RSs of a ballistic missile technology system. Others suggested external RSs including the consumer, supplier, and law (Bijker et al., 1987; Takeishi and Lee, 2005).

RSs are useful to understand not only stable, but also dynamic technology systems. For instance, Dedehayir and Mäkineif (2008) analyzed dynamics of changing RSs in personal computer (PC) games. Between the two subsystems, the central processing unit (CPU) and graphics processing unit (GPU), the RS changed. They subsequently calculated the different speeds of technology development and forecasted future RSs (Dedehayir and Mäkinen, 2011). However, with their approach, they had difficulty identifying RSs of a sophisticated technological system comprised of many subsystems because they depended on intuitive judgments.

Mulder and Knot (2001) divided a PVC technology system into lower-level subsystems, identified RSs at the level not only of a subsystem but of related subsystems and thus attempted to systematize identification. Further, they tried to identifying changing RSs as the technology system changed over time. However, most problems of expert judgments, such as subjective bias and bounded knowledge, remained unsolved. As shown in Table 1, there have been no efforts to overcome such weaknesses for ex-ante and structured identification of RSs. RS forecasting is at a very early stage, with only one previous study using simple extrapolation. Addressing these issues, our approach aims at ex-ante and structured RS identification as well as RS forecasting.

2.2. RS identification and forecasting methods

As noted above, ex-ante and structured identification of RSs might be one way of making the concept of the RS more useful and relevant for researchers, technology developers and managers. Also, the relationship between market requirements and RSs should be considered to prioritize RSs in terms of technology commercialization. As for forecasting, it should be noted that experts have been struggling to make a reliable time forecast regarding the performance of RSs. It has frequently been observed that the performance increases of RSs were slower or faster than expected (Lo et al., 2012). Quantitative methods based on historical data can be used to minimize such time errors and thus produce better forecasts by extrapolating past data into the future. However, these methods cannot consider the effects of future uncertainties that can deflect the future trend. Considering this information, there is need for a forecasting method that can minimize time scale errors and reflect future uncertainties.

Based on our methodological requirements, we select existing methods that fulfilled more than two of our requirements, as shown in Table 2. Trend extrapolation is included because it was used in recent RS forecasting research by Daim et al. (2013). Advanced expert-based methods including Delphi, scenario, and technology roadmap have the advantages of ex-ante and structured identification and future uncertainty consideration but have difficulty specifying technology-market relationships and reducing time errors (Linstone and Turoff, 2011; Meyer and Winebrake, 2009; Carvalho et al., 2013). Also, trend extrapolation is too simple to reflect future uncertainties.

MCDM (multiple criteria decision making) methods meet the requirements for RS identification. However, quantitative MCDM

Table 1
Previous RS studies.

Previous study	Technology system	RS type	Method	Ex-ante RS identification	Structured RS identification	RS forecasting
MacKenzie (1987)	Missile	Technological	Expert judgment	X	X	X
Mulder and Knot (2001)	PVC plastic	Technological Social	Expert judgment	X	X	X
Takeishi and Lee (2005)	Mobile music	Technological Social	Expert judgment	X	X	X
Murmann and Frenken (2006)	Automobile	Technological	Expert judgment	X	X	X
Dedehayir (2009)	PC game	Technological	Expert judgment	X	X	X
Daim et al.(2013)	Video game console	Technological	Expert judgment	X	X	Extrapolation

Table 2
Review of identification and forecasting methods.

Method	Classification		Requirements for RS identification and forecasting				Reference
	Qualitative/ quantitative	Normative/ exploratory	Ex-ante structured identification	Technology-market relationship	Time scale error	Future uncertainty consideration	
Delphi	Qualitative	Exploratory	O			O	Linstone and Turoff (2011)
Scenario	Qualitative	Normative	O			O	Meyer and Winebrake (2009)
Technology roadmap	Qualitative	Normative	O			O	Carvalho et al. (2013)
Quality function deployment	Qualitative	Exploratory	O	O			Wang et al. (2010)
Multi-criteria decision analysis	Quantitative	Exploratory	O	O		O	Kim et al. (2010)
Trend extrapolation	Quantitative	Exploratory			O		Daim et al.(2013)
Trend impact analysis	Quantitative/ qualitative	Exploratory			O	O	Agami et al. (2009)
Cross impact analysis	Quantitative/ qualitative	Exploratory			O	O	Bañuls andTuroff (2011)

methods such as goal programming and data envelopment analysis cannot be used when there are little quantitative data. Some qualitative MCDM methods, such as the analytic network process, are of little use when an individual expert cannot evaluate the relative importance of various criteria or RSs (Kim et al., 2010). QFD is relatively free from these problems, while satisfying the requirements and thus is appropriate for RS identification.

As for forecasting, note that RS performance is a time series of a single variable. Also, future uncertainties should be considered. Thus, there is need for a quantitative forecasting method in which a time series is modified to consider future uncertainties. Among existing forecasting methods, these requirements can be met by TIA and CIA (cross impact analysis). TIA identifies a set of important future events that can deviate from the extrapolation of historical data, judges their probabilities and impacts, and thus forecasts a range of future values rather than a single point (Agami et al., 2009). CIA estimates the potential interactions among future events and adjusts the probabilities of occurrence (Bañuls and Turoff, 2011). When experts have little confidence in quantifying such interactions, TIA is better than CIA.

Previous reverse salient studies have used expert-based methods or trend extrapolation, and thus have had some drawbacks due to missing requirements. Integrated methods of identification and forecasting including Delphi, scenario, technology roadmap are subject to a serious problem of time scale errors. Probabilistic time-series forecasting methods including TIA and CIA can minimize these errors, but cannot identify RSs. Identification-focused methods including QFD and MCDM are better than others for identification, but not for forecasting. There is no integrated RS identification and forecasting method satisfying all requirements. Combining QFD with TIA, our approach can meet all requirements, as listed in Table 2, and thus is likely to overcome the limitations of existing methods. Before explaining the methods in details, we briefly touch the technological background of CNT biosensors.

3. Technological background: CNT biosensor

A nano-biosensor is a device which can be used to detect a minute number of biomarkers, such as specific genes and proteins. It has a variety of applications including medical diagnosis, food analysis, drug discovery and environmental monitoring. In addition to nanotechnology, information and biomedical technologies are needed to further this technology (Juanola-Feliu et al., 2012). A nano-biosensor is composed of a sensitive biological element and a transducer. The former identifies a specific biomarker and then forms a bond between biomarkers and receptors of a biosensor. The latter translates the interaction of the analyte with the biological element into an electrical signal (Burg and Poulikakos, 2011).

Early biosensors combined electrochemical sensors with enzyme transducers. Then, researchers have changed the couplings of biological element and transducer. Enzyme, organelles, antibody and others were coupled to optical, mass, magnetic, thermal, electrochemical and micro-mechanical sensors (Palchetti and Mascini, 2010). Recently, advances and convergences in micro and nanoscale photonic, electronic and mechanical technologies have created an era of modern integrated biosensors including a nano-biosensor.

A nano-biosensor can be classified as either a silicone nanowire biosensor, CNT biosensor, or other type of biosensor. A CNT biosensor has excellent sensitivity and requires neither an additional marker nor an expensive optical sensing device. Thus, it is appropriate for miniaturization. With its enhanced sensitivity and reduced size, a CNT biosensor can improve the current bio-diagnostic capacity with respect to specificity, accuracy, speed and cost, and can be incorporated into wearable and implantable medical devices. It will potentially contribute to more personalized medicine as well as ubiquitous healthcare system. However, various CNT biosensors have been proposed but have not been commercialized.

The typical structure of a CNT biosensor is a combination of bio-macromolecules and CNTs in the vicinity of the electrode. The well-defined nanostructure of CNTs leads to good interaction between CNTs and enzymes (Wang, 2004). CNTs also enhance the electron transfer from the reaction center of an enzyme to the electrode. Thus, high performance can be realized.

Attracted by these properties, many companies with weak R&D capability developed CNT biosensors but could not commercialize them due to the reproducibility problem. In other words, technology commercialization failed because of unsolved technological RSs. For successful commercialization of CNT biosensors, it is obvious that the top priority should be identifying and solving technological RSs. Our method to identify and forecast RSs is explained in Section 4, and is applied to CNT biosensors in Section 5.

4. Methodology

4.1. Research framework

Our research consists of three phases, as shown in Fig. 1. Based on a review of the current literature, we define the commercialization processes of CNT biosensor as well as its key technologies

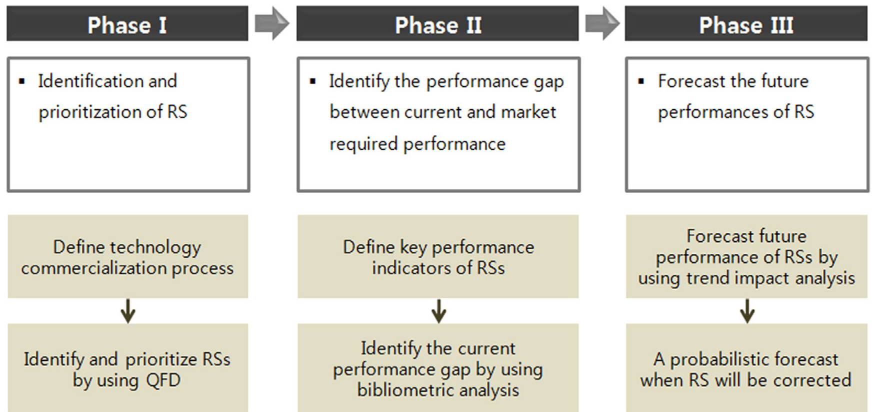

Fig. 1. Research framework.

and core physical properties. Examining all technologies and properties, six experts add, modify and delete some of these. Three CNT experts and three nano-biosensor commercialization experts identify and prioritize key RSs using QFD. As previously noted, QFD is chosen because it has the advantages of ex-ante structured RS identification and specification of technology-market relationships.

In the second phase, to understand global R&D trends of previously identified RSs, we define key performance indicators of RSs, collect relevant patents and journal articles, and plot the changing key performances over time through bibliometric analysis. We use the US Patent and Trademark Office (USPTO) database, which includes global patent applications, and Thompson Reuters' Web of Science journal database, which has global research paper submissions. Reverse salience methodology is used to identify the current performance gaps in key RSs for technology commercialization.

Then, employing TIA, we forecast a range of future values of key performance indicators of RSs. Considering technology characteristics and dynamic patterns of data, the most appropriate growth curves are selected. Key parameters of those curves are estimated using data between 2000 and 2011. Extrapolating the data, we project future performances of RSs. Our experts identify key future events and estimate probabilities of occurrence of those events with their impacts. Using these estimations, Monte-Carlo simulation produces a range of future performances including the median, 5th, and 95th percentiles. Tracking the future performance growth within the upper and lower limits, we elucidate the change in performance gap in the near future.

Through the three phases, we systematically identify and prioritize key RSs while minimizing biases in expert judgments. Also, we identify the performance gap in RSs between current and market required performance and forecast when a certain RS will be corrected.

4.2. QFD

QFD is a method originally developed in order to reduce some biases in expert judgments and also to systematically identify RSs (Cohen, 1995). In 1966, it was first developed to translate customer requirements into engineering characteristics. Since it proved effective for Mitsubishi Heavy Industries and Toyota in the 1970s, it has been used mainly for product development in a wide array of industries (Sullivan, 1986). Its use has extended to rating the importance of methods (how) for achieving goals (what), and therefore it has been used in various disciplines including R&D and policy. Also, there have been several efforts to improve the basic method. For instance, the axiomatic design by Suh (2001) has advantages for analyzing the transformation of customer needs into not only functional requirements, but also design and process variables and thus has been useful for the design of complex products.

The first phase in the implementation of QFD usually involves development of a House of Quality. This method utilizes a planning matrix to relate customer requirements on the left to product features across the top. First, experts rate the importance of customer requirements. Then, they engage in discussion, rate the correlations between product features and customer requirements, typically using the standard QFD scale composed of 1 (weak), 3 (medium), and 9 (strong), and input the scores into the matrix. For each product feature, a weighted sum of the importance of customer requirements and the correlation is calculated. The higher is the weighted sum, the more important is the product feature.

Similarly, for technology commercialization, customer requirements can be replaced by market requirements, and product features can correspond to key technologies. Experts rate the importance of market requirements and relevance between market requirements and key technologies using the 1-3-9 scale. Note that the relevance score should be low if there are no technological RSs. Thus, a weighted sum of importance and relevance scores for a key technology represents the importance of the technology for commercialization, measuring the priority of its RSs.

Alternative methods have been suggested, including ontology-based inference and the technology tree. However, QFD is more appropriate than the others for technology commercialization research because it considers both technology and market perspectives.

4.3. Bibliometrics

Bibliometrics is defined as the quantitative study of publications as reflected in bibliographies (White and McCain, 1989). Researchers have used bibliometric methods to analyze science and technology literatures, including patents and journal papers, because the use of global large-scale bibliometric data can reduce subjective and local biases frequently observed in expert judgments (Porter and Detampel, 1995; Van Raan, 2005). Over the decades, bibliometric methods have been widely applied in technology management areas including technology opportunity and evaluation (Meyer, 2001; Van Raan, 2006).

Bibliometrics has proven to be useful to analyze macro-phenomena such as technological megatrends (Kostoff et al., 2007). Yet, it is not appropriate for a detailed analysis of specific technologies due to the limitations of bibliometric indicators, including the number of documents and number of citations

(Costas and Bordons, 2007). For instance, using the number of patents, we can identify some technological domains in which companies have made greater commercialization efforts, but we have difficulty identifying a specific technology in terms of key performances and commercialization factors without qualitative analysis by experts (Moed and Burger, 1985). Put briefly, we cannot count only on bibliometric indicators to make specific R&D decisions in practices.

Considering this information, we combine bibliometrics with QFD, capitalizing on the advantages of both methods. Biases in expert judgments can be reduced by both QFD and bibliometrics. Also, for a detailed analysis of both technology and RSs, experts define key performance indicators (KPIs) of RSs with the minimum required performance for technology commercialization. Using keywords of KPIs, we collect relevant journals and patents and plot the changing performances over time. A current performance gap is defined as the difference between the current and minimum required performance. This enables us not only to identify the current difficulty of solving RSs, but also to forecast future RSs.

Bibliometric indicators, however, have been frequently criticized for being outdated (Hall et al., 2001). Patents take 2–4 years to be granted, and journal papers take time to be published. To reduce such truncation problems, we use patent application and paper submission data rather than grant and publication data.

4.4. Trend impact analysis

Gordon (2009) developed TIA to address criticism of the quantitative forecasting methods based on historical data. These methods, from simple extrapolation to various time-series techniques, produce forecasts by extrapolating historical data, suffering from a common weakness of ignoring the effects of future uncertainties. It has frequently been observed that future uncertainties can impact relationships and thus affect the expected trend. As a remedy, TIA was suggested as a forecasting method in which a time series is modified to consider perceptions of how future events may change extrapolations.

The TIA process is comprised of two principal steps: (1) a curve fitting to historical data without any consideration for future events and (2) expert judgments for identification of important future events and probability estimation of the occurrence of those events as a function of time and expected impact. These judgments can be elicited by other qualitative forecasting methods including environmental scanning and Delphi (Gordon and Glenn, 2009; Linstone and Turoff, 2011). Combining the probabilities and impacts of future events with the results of the extrapolation, TIA produces a range of possible future values including upper and lower limits at determined probability levels. A typical range is between the 5th and 95th percentiles. Simulation techniques such as Monte Carlo simulation are used to estimate upper and lower limits.

TIA is well suited for policy evaluation for managers wishing to modify the course of a specific time-series indicator. Managers can analyze the effect of a certain policy on the indicator by changing the probabilities and impacts. Also, TIA enables managers to calculate the probability that current strategic targets will be met over the coming years. Thus, it has been used in many organizations, including the US National Science Foundation and US Department of Energy. Recent studies have combined TIA with other methods, including neural network (Agami et al., 2009) and fuzzy logic (Agami et al., 2010), compensating for the incomplete identification of future events and inaccurate estimation of probabilities and impacts.

The future performance of RSs can be influenced by future events that may change extrapolations based on historical performance data. For instance, if unexpected new production equipment is developed and used, it can increase future performance of some RSs more than is expected. Experts involved in the QFD process can identify key future events and also estimate their probabilities of occurrence and their impacts. TIA can consider future uncertainties while avoiding the risk of simple extrapolation, and thus it is appropriate for forecasting the future performance of RSs.

4.5. Judgments by a panel of experts

Expert judgments have been used in several identification and forecasting methods including Delphi, Scenario, Roadmap, MCDM and others. Given some problems, experts are required to give qualitative or quantitative judgments, and the final aggregate is taken as the output. Despite effective in many practices, expert judgments have several deficits, such as subjective biases of experts and negative effects of interactions among experts (Landeta, 2006). In our approach, QFD is a method not only to reduce such biases, but to satisfy methodological requirements comprising ex-ante and structured identification and balanced view of technology and market.

However, methodological weaknesses of expert judgments remain, including normative social influence and group conformity (Bolger and Wright, 2011). A structured brainstorming technique is useful to reduce such deficits when experts focus on a particular subject (Byrne and Barlow, 1993). It proceeds through four phases: (1) problem statement, (2) individual generation of ideas, (3) collective organization of ideas, and (4) collective evaluation and selection of ideas. It separates idea generation from collective evaluation process, therefore reducing negative effects arising from social interactions of experts. Also, we make the process workshop-based and neutrally facilitated, and thus encourage participation and positive mutual reinforcement (Kerr et al., 2013). The selection of experts is as important as the process, and will be explained in the next section.

5. Empirical analysis and results

5.1. Data

Our method requires several experts and bibliometric data. As previously noted, six experts are involved in identifying and prioritizing RSs of CNT biosensor commercialization for three six-hour days. The panel of experts is comprised of a university researcher, a researcher from a private company in Korea, a researcher from a governmental electronics research institute, and three biosensor commercialization experts from private companies in Korea. Three CNT experts hold Ph.D. degrees in engineering. Each has more than ten years of R&D experience. With degrees in either management or chemistry, the three commercialization experts also have been in charge of technology commercialization over the last decade. These experts also review the results of bibliometric analysis and forecasting.

For bibliometric analysis, we use USPTO and Thompson Reuters' Web of Science databases to collect patents and journal papers published between 2000 and 2011. As a result, 7439 patents and 42,000 papers are collected using keywords such as CNT, SWCNT, and other similar and relevant words. Again, using keywords of key performance indicators, we extract patents and papers with key performance information of top priority RSs.

5.2. RS identification

Reviewing previous studies of 42,000 papers, we define four commercialization processes comprising material research, production

Fig. 2. CNT biosensor commercialization process.

Phase 1		Phase 2						Phase 3		Phase 4		
Material research		CNT production technology development						Application technology development		Commercialization technology development		
Structure	Physical property	Synthesis (quality)	Synthesis (capacity)	Shape separation (purity)	Shape separation (capacity)	Electrical property separation (purity)	Electrical property separation (capacity)	Device fabrication	Sensing material combination	Sample pre-processing	Electrode optimization	Signal processing
A1	A2	A3a	A3b	A4a	A4b	A4c	A4d	A5	A6	A7	A8	A9

Fig. 3. Process-wise key CNT biosensor technology.

technology development, application technology development, and commercialization technology development, as shown in Fig. 2 (Fam et al., 2011; Wartburg and Teichert, 2008). According to Jolly (1997), the technology commercialization process is sequential, meaning that it cannot proceed to the next phase without solving problems in the current phase. If key technologies in some preceding processes cannot meet the minimum required performance, commercialization of CNT biosensors will fail in later processes.

Previous studies suggest seven key technologies comprising high purity SWCNT synthesis and separation, device fabrication, sensing material combination, sample pre-processing, electrode optimization, and signal processing (Lee, 2008; Saeed, 2010). Given seven key CNT biosensor technologies from the literature review, six experts engage in discussion and identify key technologies in each commercialization process.

Among these key technologies, high purity SWCNT synthesis is regarded as the top priority (Li et al., 2008; Yang et al., 2010). Several scholars argue that length, diameter, electrical properties, and purity of SWCNTs produced under the same conditions can vary (Jacobs et al., 2010; Yang et al., 2010). Such non-uniformity is a major threat to commercialization. Others point out the difficulty of obtaining high purity SWCNT with specific helicity and emphasize the necessity of technologies to change physical and chemical properties (Vashist et al., 2011; Wang, 2004). To date, it is possible to produce a small amount of high purity SWCNT with specific helicity. However, on a large scale, the unit price of such SWCNTs would soar above an acceptable level and thus become a commercialization barrier (Fam et al., 2011). Considering this information, our experts divide high-purity SWCNT synthesis and separation into six sub-technologies and include structure and physical property technologies to the material research process. As shown in Fig. 3, 13 key technologies used in the CNT biosensor commercialization processes are identified, including six sub-technologies.

Note that all key technologies should meet the market requirements for commercialization. Through the literature review and experts brainstorming, nine market requirements are identified and then categorized into performance, practicality, economics, and regulation subsets, as shown in Table 3. A structured brainstorming technique is used because we focus on a particular subject (Byrne and Barlow, 1993). Six experts are individually asked to adopt their own perspectives and then to state important market requirements within a period of 30 min. Having examined a multi-perspective point of view, they collectively categorize, evaluate, and fix market requirements over a period of two hours.

In Fig. 5, the derived market requirements correspond to goals in QFD and thus are designated in the left column in the category of House of Quality. Key technologies are used to achieve those goals and accordingly appear in the upper row. Using the standard 1-3-9 scale, six experts rate the importance of market requirements and the difficulty of achieving market requirements through key technologies. Thus, a weighted sum of importance and difficulty score at the bottom represent the priority of RSs. The higher is the score, the more difficult and important is the RS.

Experts reach a consensus on the importance level of market requirements as a result of sufficient discussion during the brainstorming session. Then, they are individually asked to rate the difficulty score and show some differences in individual scores. Discussing the causes of varying scores, they fix the final scores. New information from other experts is of great use to facilitate this process. For instance, there are more 1 or 3 scores than in Fig. 4, but new production technology information makes experts change those scores to zero.

A4c (high purity SWCNT separation with specific electrical properties) receives the highest score, whileA4d, A5, A6, and A7 score higher than 80. These RSs are important for commercialization but difficult to solve, forming the key RS group. Other RSs are of relatively little importance with scores less than 40. Note that CNT biosensor commercialization cannot proceed without solving prior RSs. Therefore, A4c and A4d in the CNT production technology development process are given top priority.

5.3. RS bibliometric analysis and forecasting

Although key RSs are identified, the gaps between current and minimum required performance cannot be determined. Bibliometric analysis of patents and journal papers can help illustrate not only current performance gaps, but also dynamics of changing gaps. The first step in this process is to define KPIs of RSs. Combining the literature review with expert judgments, we define the KPI of A4c (high purity SWCNT separation with specific electrical properties) as a semi-conductive SWCNT purity, and we define the KPI of A4d (mass high purity SWCNT separation with specific electrical properties) as the semi-conductive SWCNT scale. The market required minimum performance is derived from the literature review on recent studies and is examined and confirmed by six experts. Definitions and measurement units are as shown in Table 4.

Table 3
Market requirements for CNT biosensor commercialization.

	Category	Requirement	Notation
Market requirements for commercialization	Performance	Selectivity	B1
		Sensitivity	B2
		Speed	B3
		Multiplex sensing	B4
	Practicality	Reproducibility	B5
		Miniaturization	B6
		Lifecycle	B7
	Economics	Price	B8
	Regulation	Safety (no toxicity)	B9

				CNT-biosensor commercialization core technology												
				Phase 1		Phase 2						Phase 3		Phase 4		
			Importance level	Material research		CNT production technology development						Application technology development		Commercialization technology development		
				A1	A2	A3a	A3b	A4a	A4b	A4c	A4d	A5	A6	A7	A8	A9
Market requirements for commercialization	Performance	B1	1	3	3	0	0	1	0	9	0	3	3	3	1	1
		B2	1	0	0	0	0	0	0	0	0	0	9	3	0	0
		B3	3	0	0	0	0	0	0	0	0	0	0	9	0	1
		B4	3	0	0	0	0	0	0	0	0	0	9	0	3	1
	Practicality	B5	9	0	0	3	0	3	0	9	0	3	1	0	0	0
		B6	3	0	0	0	0	0	0	0	0	0	0	9	0	1
		B7	3	0	0	0	0	0	0	0	0	9	3	0	0	0
	Economics	B8	9	0	0	0	3	0	3	0	9	3	3	3	3	0
	Regulation	B9	1	9	9	0	0	0	0	0	0	0	0	0	0	0
Reverse salient				12	12	27	27	28	27	90	81	84	84	87	37	10

Fig. 4. CNT biosensor QFD.

Table 4
Reverse salient key performance indicators.

RS KPI	RS KPI definition	Measurement unit
Semi-conductive SWCNT purity	A mass ratio of semi-conductive SWCNT with specific electrical properties after separation	%
Semi-conductive SWCNT separation scale	Mass of metallic and semi-conductive SWCNT mixtures for separation	Mg

Among 7439 patents and 42,000 papers, using a set of KPI keywords as queries, we collect 95 USPTO patents and 18 Web of Science journal papers including KPI information. Using these patents and papers, we plot the changing three-year moving averages of KPIs between 2000 and 2011. The publication of older research results before more recent findings due to time differences of paper reviews and patent examinations cause KPIs to fluctuate. To reduce such fluctuation, we use a three-year moving average.

As shown in Fig. 5, we plot the changing performance of semi-conductive SWCNT purity, which gradually increased from 82% in 2004 and stabilized around 95% in 2008. The market required minimum purity for most biosensors is 95%, meaning that market requirements were almost met in 2008. The purity should be greater than 99% only for biosensors inserted into a human body. The market share of these biosensors is expected to be less than 5%. Thus, RS of A4c (high purity SWCNT separation with specific electrical properties) was almost solved around 2008. For some biosensors, the current performance gap in purity is 4%.

Given the three-year moving average data of purity, we employ an extrapolation method to forecast when the purity will reach 99%. Among several curves, a logistic curve is chosen because the data shows a typical pattern of a logistic curve with the known upper limit of purity (99%). Its formula is shown below.

$$y = (1/L + c \times b^{t})^{-1} \tag{1}$$

Assuming that an upper limit of purity denoted by L is 99%, we can estimate , as shown in Table 5. Parameter estimates are statistically significant at the 1% level. A high R^2 (0.988) with a

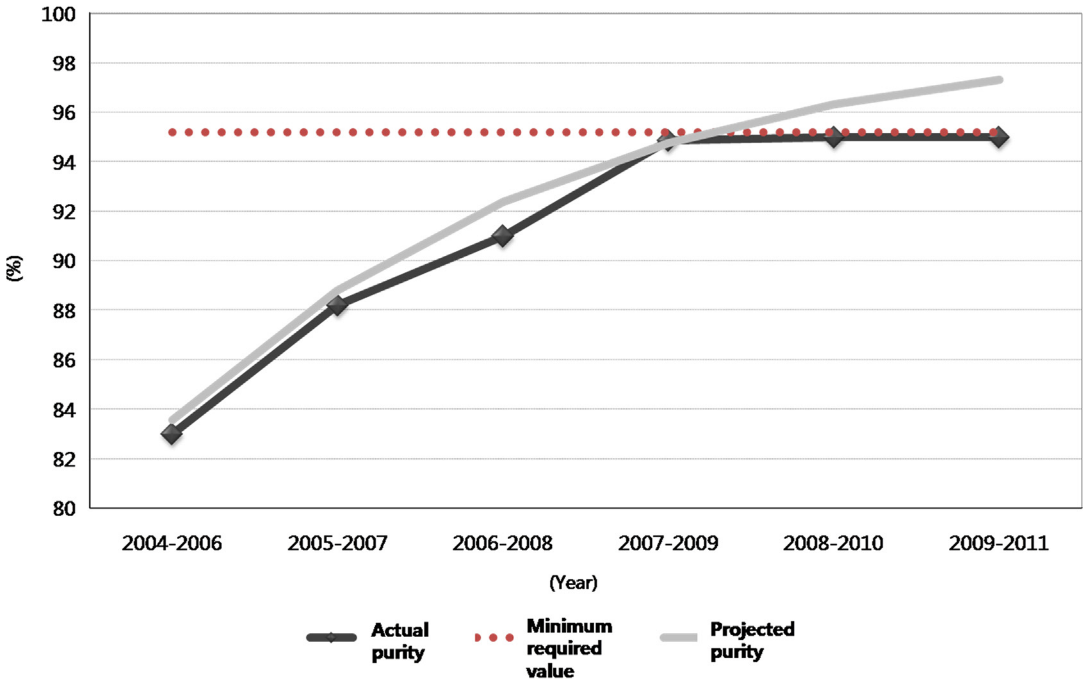

Fig. 5. Semi-conductive SWCNT purity trend and future projection.

Table 5
Parameter estimation results of a semi-conductive SWCNT purity growth curve.

	Coefficient	Standard deviation	T	*p*-Value	F	*p*-Value	R^2
b	0.619	0.033	18.926	0.003	82.495	0.012	0.988
c	0.003	0.000	6.911	0.02			

Table 6
Parameter estimation results of a semi-conductive SWNT separation scale growth curve.

	Coefficient	Standard deviation	T	*p*-Value	F	*p*-Value	R^2
b	0.311	0.38	8.211	0.001	67.42	0.01	0.944
c	25.090	3.698	6.785	0.002			

p-value of 0.012 indicates that the logistic curve is a good fit with the data.

Using this logistic curve, we forecast the future values of semi-conductive SWCNT purity, which is expected to reach 98% by 2011 and 99% by 2013. Contrary to forecasting results, however, the purity has not increased since 2008. To identify the reason in more detail, we plot the three-year moving average of the annual number of patents and journal papers with semi-conductive SWCNT purity information, as shown in Fig. 6. The number of journal papers reached a peak around 2004 and has continuously decreased since then. The number of patents shows a similar pattern with a later peak in 2006. In other words, basic science reached its limits in 2004, and applied science reached its performance ceiling in 2006. Then, both entered a declining period with little technological innovation. Qualitatively reviewing recent papers, six experts confirm that there has been no new separation technology since centrifugation technology was developed in 2005. Finally, as previously noted, the market share of CNT biosensors, which require a purity greater than 99%, is less than 5%. Therefore, the purity of semi-conductive SWCNTs is not likely to exceed 95% in the near future and will remain an RS for CNT biosensors inserted into a human body.

A mass high purity SWCNT separation with specific electrical properties is the second most important RS and is rated on a semi-conductive SWCNT scale. Through bibliometrics analysis, the changing performance of this RS is plotted between 2004 and 2011. By 2004, the separation scale was between 1 mg and 10 mg. Then, it increased rapidly and reached around 150 mg by 2011. However, the minimum required separation scale for commercialization is 10,000 mg (10 g). At an early stage of performance growth, the separation scale is affected by several future uncertainties.

Thus, we employ TIA to modify the future trend by reflecting key future uncertainties. The historical performance data during 2004–2011 are extrapolated to 2020. The performance growth curve is expected to become steeper with an unknown limit. Considering these predictions for the pattern of data, we choose an exponential curve whose formula is shown below.

$$y = c\,\exp(bt) \tag{2}$$

The estimation results of key parameters are given in Table 6. All estimates are statistically significant at the 1% level. A high R^2 (0.94) with a *p*-value of 0.01 indicates adequate curve selection.

Given this forecast, six experts identify key future events that could change the curve and judge the occurrence probabilities of these events and their impacts by 2020. They are individually asked to complete these tasks and then collectively finalize the figures, as shown in Table 7. Experts are certain of the improvement in CNT technologies, including separation methods and production, but also identify two external threats: (1) progress in competitive nano-material development and (2) decreasing R&D investment.

Using these judgments, we run a Monte-Carlo simulation. For each event, a random number is generated. If the probability of an event in a given year exceeds the random number, the event is considered to occur. The impacts of all the occurring events are summed to determine the total impact on the extrapolated curve in a given year. The results are recorded, and the process is repeated 500 times. Each

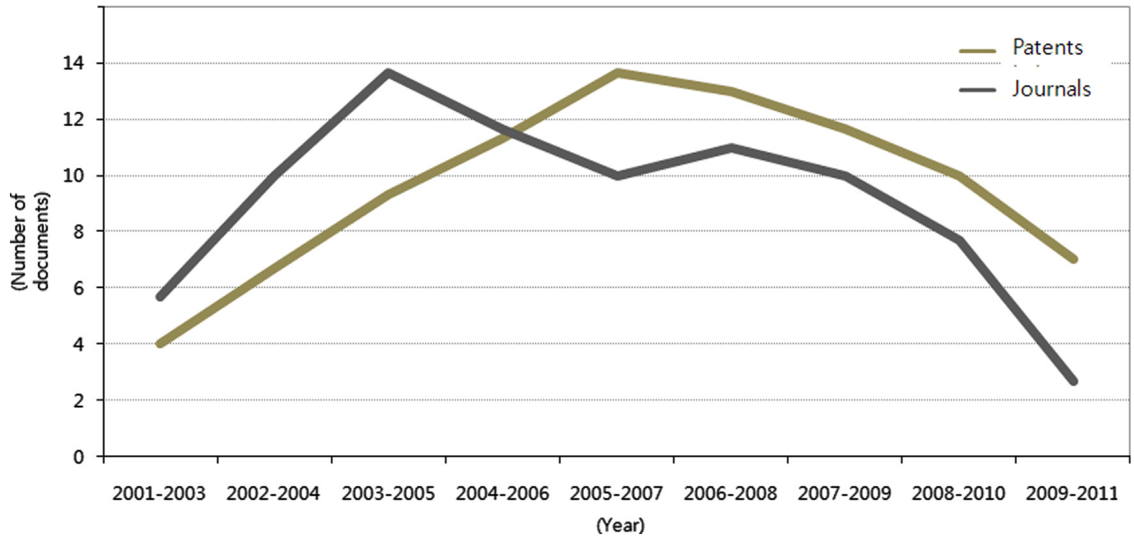

Fig. 6. Numbers of patents and journal papers regarding semi-conductive SWCNT purity.

Table 7
Expert judgments of key future events, probabilities, and impacts for TIA.

Event	Maximum impact (%)	Years to first impact	Years to maximum impact	Probability by 2015 (%)	Probability by 2020 (%)
Introduction of new effective separation method	40	5	8	25	45
Improvement of CNT production equipment	25	3	7	50	60
Complementary technology development	10	1	10	40	50
Progress of competitive nano-material	−50	6	10	15	40
Rapid expansion of biosensor market	20	4	11	5	30
Decreasing R&D investment for CNT	−45	1	6	50	65

of these 500 runs is considered a mini-scenario, i.e., a single future projection. Generating 100 future projections allows to formation of a range of future projections including the 5th and 95th percentiles.

As shown in Fig. 7, future events create a lopsided range of uncertainty toward the upper limit, positioning the median beyond the original extrapolation. This means that the separation scale could reach the market required level earlier than is expected by extrapolation. Along the 95th percentile curve, the market required level can be met in 2017 if positive events dominate negative ones. Contrastingly, the 5th percentile curve cannot reach the required level before 2020.

For two high priority RSs of CNT biosensors, we identify the current performance gap between current and minimum required performance and further forecast the future performance gaps. The top priority RS, A4c (high purity SWCNT separation with specific electrical properties), is almost solved. However, the second priority RS, A4d (mass high purity SWCNT separation with specific electrical properties) shows a severe performance gap and will not be solved before 2017. Thus, the semi-conductive SWCNT separation scale is, and will be, the largest obstacle to CNT biosensor commercialization. Technological innovation efforts should be concentrated on this RS.

6. Conclusion

This study suggests a new and systematic way of identifying and forecasting RSs of emerging technologies using a sequential combination of QFD, bibliometrics, and TIA. QFD enables several experts to systematically identify and prioritize RSs while reducing several biases in expert judgments. Bibliometrics help us not only collect highly relevant scientific and technological information, but also identify the performance gaps of RSs between current and minimum required performance. Going a step further, we make probabilistic forecasts of the future performance gaps using TIA, therefore indicating when technological obstacles can be overcome.

Conceptually, our approach builds on an emerging system's concept of technology (Sahal, 1981). Sahal (1985) suggested that technological innovation should arise from a process of differential growth whereby the parts and the whole of a system do not grow at the same rate. Choices about components, methods, and theories are made to solve these technological constraints, improving the technological system. The evolving paths, i.e., technological trajectories, are created by new logic of design (Clark, 1985), technological guideposts (Sahal, 1985), creative combination of existing technologies (Arthur, 2009), and other methods. Despite many previous studies on frameworks, models, and cases, there has been little effort to identify key technological constraints using large amounts of data. Tackling this issue, our study is intended to spur analysis of the recursive process of technology evolution between constraints and solutions.

From a practical standpoint, using our method, corporate managers can identify current and future RSs and thus make better R&D decisions with due regard to technological RSs. In other words, our method can optimize R&D portfolios in terms of commercialization, improving R&D productivity. Although internal experts can identify RSs, they often underestimate or overestimate RSs due to a variety of reasons including bounded knowledge and subjective bias. Combining QFD with specific bibliometric analysis, our method helps internal experts systematically reach a consensus on key RSs. Moreover, definition and measurement of the KPIs of RSs enable corporate managers to monitor globally changing performance of RSs; therefore, increasing the effectiveness of R&D strategies and planning.

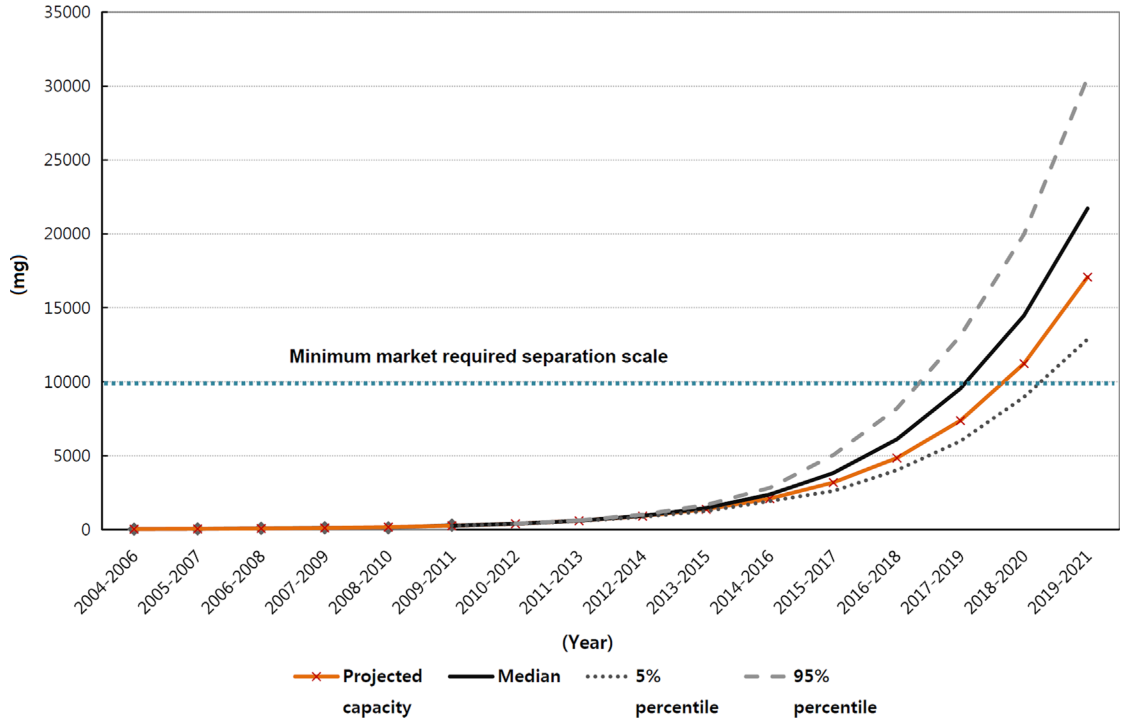

Fig. 7. TIA of semi-conductive SWCNT scale.

TIA helps managers identify key future uncertainties and events and further calculate the probability that important technological obstacles will be removed over the coming years.

From an academic perspective, the primary contribution of this paper is ex-ante identification of top-priority technological RSs. Previous studies have focused on ex-post identification and thus are of little help to identify current bottlenecks in the process of technology commercialization. A joint use of QFD and qualitative bibliometrics makes possible such ex-ante identification and prioritization. Previous studies have had difficulty defining and measuring specific RSs. An integration of QFD and bibliometric analysis enables us not only to define a specific KPI of an RS, but also to identify the performance gap of KPIs between current and minimum required performance, therefore overcoming such weaknesses. Further, considering future uncertainties and events, we forecast a range of future RS performance values between the upper and lower limits with regard to the reduction of time errors.

Our approach is based on historical bibliometric data and thus is of little use when an emerging technology is at a very early stage because few data are available. Expert-based methods such as Delphi and scenario analysis are relatively free from such constraints and thus are more appropriate forecasting methods under such conditions. Bibliometric data become available to identify and forecast technological paradigms when competing paradigms appear (Kuusi and Meyer, 2007). Thus, our approach is first useful at an early development stage and becomes increasingly effective as technology commercialization proceeds. However, at the later stages, other non-technological problems are expected to more highly affect commercialization than are technological RSs. Hybrid methods of expert-based and large data-based methods are appropriate. Overall, our approach is most useful for emerging technologies in early- and mid-development stages.

Six experts who participate in QFD and TIA are asked the merits and demerits of our approach. Appreciating the ex-ante specific identification of RS, they come to the consensus that it can be useful in actual R&D planning because top priority should be given to a technology for which RSs can be most readily overcome. Also, they have experience reducing the misidentification of RSs as well as market requirements due to bounded knowledge and subjective bias. The set of individually identified RSs and market requirements is different from a finalized set after QFD, providing evidence of reduced misidentification. However, the experts commonly point out that the method is very time-consuming and requires the assistance of several experts, suggesting the use of information and communication technologies to improve efficiency. Also, the estimation of future events, probabilities, and impacts can vary with the knowledge and experience of experts, communication techniques, and other elements and thus needs to be designed carefully.

Our approach also has several limitations. Above all, bibliometric analysis of patents and journal papers reduces several biases in expert judgments on technological RSs using KPI data. However, minimum market requirements depend heavily on expert judgments and thus are not free from biases. Also, our RSs are externally imposed by experts, and therefore some RSs that emerge from within the technological system can be ignored. Methods for defining and measuring market requirements need to be investigated. Also, TIA has limitations for forecasting the future of disruptive technologies characterized by breaks and explosive growth, which is true of many emerging technologies. Therefore, we should find and use appropriate methods such as system dynamics and agent models for disruptive technologies. Finally, our method might be of little use to short lifecycle technologies because of the time-lag problem of bibliometric data.

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Appendix A1

See Table A1.

Table A1
Yearly average of RS KPIs.

	Semi-conductive SWCNT purity (%)	Semi-conductive SWCNT separation scale (mg)
2004	76	50
2005	89	17
2006	84	21
2007	89	105
2008	95	135
2009	95	–
2010	95	100
2011	95	500

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