Technology Roadmapping for Competitive Technical Intelligence

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Abstract

Understanding the evolution and emergence of technology domains remains a challenge, particularly so for potentially breakthrough technologies. Though it is well recognized that emergence of new fields is complex and uncertain, to make decisions amidst such uncertainty, one needs to mobilise various sources of intelligence to identify known-knowns and known-unknowns to be able to choose appropriate strategies and policies. This competitive technical intelligence cannot rely on simple trend analyses, breakthrough technologies have little past to inform such trends, and the directions of evolution are difficult. Neither do qualitative tools, embracing the complexities, provide all the solutions, since transparent and repeatable techniques need to be employed to create best practices and evaluate the intelligence that comes from such exercises. In this paper, we present a hybrid roadmapping technique that draws on a number of approaches and integrates them into an approach that can be applied to breakthrough technology fields and integrates a multi-level approach (individual activities, industry evolutions and broader global changes). We describe this approach in deeper detail with a case study on dye-sensitized solar cells. Our contribution to this special issue is to showcase the technique as part of a family approaches which are emerging around the world to inform strategy and policy.

Keywords Technology Roadmapping; Competitive Technical Intelligence; Text Mining; Tech Mining.

Highlights

1) Insights into developments in hybrid quantitative/qualitative approaches to technology roadmapping and their applications for strategy and policy;
2) The development of selection and evaluation criteria for practical roadmapping approaches suitable for real-world situations;
3) Application of adaptive technology roadmapping models for the production of competitive technical intelligence, including the engagement of ST&I factors, emerging technology-oriented empirical study;
4) Insights on the approach via application to the field of dye-sensitized solar cells.

Introduction

Technology Roadmapping (TR) is a future-oriented strategic planning device (Winebrake 2004) that provides a structured approach to help identify relationships between existing and developing technologies, products, and markets over time (Phaal et al. 2004). If one take socio-technical change as three interlinked, but distinct, layers (Rip and Kemp 1998), it is reasonable to classify TR endeavours by scope related to these three layers: 1) TR for national Research & Development (R&D) planning to inform policy involving economic, scientific, technological, and innovation landscapes; 2) TR for industries and sectors, which focus on existing and potential collaborations and collective coordination in target technological areas; 3) TR for specific technological trajectories (Zhang et al. 2013).

Over the past years, our colleagues from Georgia Institute of Technology's Program in Science, Technology, and Innovation Policy and Beijing Institute of Technology's Knowledge Management and Data Analysis Lab have been pursuing Tech Mining (Porter and Cunningham 2004) and Technology Opportunities Analysis (Porter and Detampel 1995) research to analyze Newly Emerging Science and Technologies (NESTs). One such collaborative endeavour focused on "Forecast Innovation Pathways" (FIP) to help capture and project developmental trends for a specific technological field, assessment application prospects, and pose options for private and/or public decision makers (Robinson et al. 2013b). A combination of text mining techniques contributes to FIP (Guo et al. 2012). We have applied the FIP approach to deal with real-world NEST concerns, including nano-enhanced solar cells (Porter et al. 2010), nano-enabled biosensors (Huang et al. 2012), hybrid & electric vehicles (Porter et al. 2013), and nano-enabled drug delivery (Robinson et al. 2013a). These FIP efforts share targets with TR, but pay more attention to foresight aspects. Nevertheless, it is still logical to consider FIP as a parallel form of TR.

Due to the strategic emphases, expert knowledge still plays a determinant role in TR and the development of TR remains a largely qualitative task (Geum et al. 2015). Traditional text mining techniques, although widely applied for technical characterization, mainly defer to expert contributions in devising TRs (Kostoff et al. 2004). Phaal et al. (2004) summarised fourteen examples of general TR cases to offer a guidebook for TR alternatives. There are also quite a few TRs that rely on quantitative methods with diverse emphases (Gerdsri and Kocaoglu 2007; Lee et al. 2009a; Huang et al. 2014; Zhou et al. 2014; Geum et al. 2015). However, there are still no adaptive criteria and metrics for the evaluation of TRs; existing ones tend to be limited within particular systems. This paper thus focuses on the following research questions:

1) How to balance qualitative and quantitative methodologies to inform TR regarding key components and their relationships?

2) Which criteria and metrics can be used for the evaluation of the efficacy of alternative TRs?

3) How is TR related, similar to and different from technology foresight projects?

The theme of seeking suitable balance between qualitative and quantitative methodologies runs through the entire paper. We also emphasize the strategy and target-driven criteria for TR selection and evaluation. In this paper, we address concerns of Competitive Technical Intelligence (CTI) (Porter and Cunningham 2005) and aim to develop a series of TR models that balance qualitative and quantitative methods. First, based on traditional text mining techniques and a "Term Clumping" stepwise process (Zhang et al. 2014a), we present a term/topic-based TR composing model (Zhang et al. 2013) that highlights the interaction between core technological components. Then, we introduce Subject – Action – Object (SAO) analysis and the Contradiction Matrix concept of TRIZ theory to retrieve Problem & Solution (P&S) patterns (Zhang et al. 2014b). Those can contribute to a problem-solving sequence for technological evolutionary pathways in P&S pattern-based TR model. In parallel, we apply Fuzzy Set (Zadeh 1965) to transfer rough expert knowledge to defined numeric values. This can help generate TR automatically (Zhang et al. 2015).

This paper draws on Science, Technology & Innovation (ST&I) data to generate historical TRs. Such summarization of developmental patterns can inform R&D program management. Our model is to then seek approaches, e.g. expert knowledge, trend extrapolation, and quantitative methods, to get from the historical data-based TRs to forecast future developmental trajectories. Referring to the above TR models, we propose criteria for TR selection and evaluation on target technologies, compare foci, and take various ST&I factors into consideration – e.g. Triple Helix model that emphasizes government – industry – academy relationships (Etzkowitz and Leydesdorff 1995; Etzkowitz and Leydesdorff 2000) or the GUISPs model that focuses on the Government – University – Industry Strategic Partnerships (Robinson 2009); incorporation of multiple ST&I data types (Zhang et al. 2015); and attention to

Technology Delivery System (TDS) for market/user, R&D and manufacturing factors (Robinson et al. 2013b).

This paper is organized as follows – the Related Works section reviews previous studies on qualitative and quantitative methods for TR. The Methodology section presents three models for composing TRs – Term/Topic-based TR, P&S Pattern-based TR, and Fuzzy Set-based Automatic TR. The Empirical Study follows, applying our TR models to Dye Sensitized Solar Cells (DSSCs) to profile technological evolutionary pathways and foresee possible trends in the near future. We summarize the criteria that could be used for TR selection and evaluation and discuss the similarity and difference between TR and other foresight projects in the Discussion section. Finally, we conclude our research and outline future research priorities.

Related Work

This section reviews TR-related previous literatures on Qualitative Method-based TR, Quantitative Method-based TR, and Hybrid TR.

Qualitative Method-based TR

Since Motorola and Corning firstly applied TRs for commercial strategy and technology evolution and positioning studies (Robinson and Boon 2014), TR has become a powerful instrument for supporting strategic planning, which holds on mighty capabilities on exploring the dynamic relationships between technological resources, organizational objectives and the changing environment (Phaal et al. 2004). Qualitative methods, e.g. expert interview, Delphi, scenario planning, discussion/seminar/workshop, still take leading roles in TR's construction and implementation, and usually contain academic researchers, industrial stakeholders, and government officials (Garcia and Bray 1997; Phaal et al. 2004; Winebrake 2004; Zhang et al. 2013).

As a pioneer of TR studies, Sandia National Laboratories constructed fundamental criteria and schemes for roadmapping (Garcia 1997; Garcia and Bray 1997), and this 3-phase process and its modified versions were applied in a large range of emerging technologies, e.g. microsystem and nano-system (Walsh 2004), semiconductor silicon industry (Walsh et al. 2005), and pharmaceutical technology (Tierney et al. 2013). Aiming to outline a general guidance to adapt wider strategic needs, Lee and Park (2005) firstly developed a modularization method-based TR customizing function, Robinson and Propp (2008) designed a catalogue for technology management-oriented analytic, Tran and Daim (2008) laid out technology assessment-related approaches onto defined levels of public decision making domain and business and non-government domain, and then, Stirling (2008) proposed a core roadmapping framework which provided flexibility for multiple strategic perspectives or a hierarchical family of roadmaps.

What is clear is that, although quantitative methods are increasingly applied to computation, they are outweighed by qualitative method-based TR which remain the mainstream of current TR activities and especially real-world applications, e.g. manufacturing industry (Gerdsri et al. 2009), internet security technologies (Fenwick et al. 2009), produce-service integration(Geum et al. 2011), car-sharing service (Geum et al. 2014), transparent display (Jeong and Yoon 2015). One reasonable understanding for the popularity of qualitative method-based TR would likely be that expert knowledge affords powerful creditability to take responsibility for the results, although there is always an expert biased which would well be counterbalanced by quantitative approaches.

Quantitative Method-based TR

Text mining as well as bibliometric, scientometric, and informetric techniques have been used to help experts to retrieve textual elements for ST&I studies since the 1990s (Kostoff et al. 2004), but computer-based graphical techniques were firstly introduced to convey information to users and provide constructs for developers (Walsh 2004). Now, the development of high intelligent information techniques, e.g. artificial intelligence, pattern recognition, and machine learning, dramatically increases the capability to identify and visualise potential relationships automatically, although this kind of attempts is still far away from large-scale applications.

Narrowing our focus on ST&I text analyses, a technique which is widely recognized is to retrieve topics via textual element, e.g. words, terms, or phrases, and identify their relationships via defined association rules. There has been a substantial contribution in the form of automatic techniques, although most of them could only be defined as quantitative methods for information extraction and visualization rather than strictly quantitative method-based TR. As an example, based on co-occurrence analysis, Zhu and Porter (2002) developed an automatic approach to extract and visualise information

for network analysis; Chen (2006) developed a generic approach to detect emerging trends from co-citation networks and applied for visualising TR automatically; Waltman et al. (2010) defined an association link to blend linkages, e.g. co-occurrence, co-citation, and bibliographic coupling, and visualised grouped nodes as networks. In parallel, novel statistical techniques also started to occupy position on historical data-based trend analysis, e.g. Allan et al. (1998) proposed approaches to find and follow new events in a stream of broadcast news stories, Kim et al. (2009) complemented a probabilistic approach to retrieve linguistic relationships from patents and discover technological trends, and Blei (2012) applied Topic Model algorithm to analyze all of *Science* magazine from 1880 to 2002.

Today, the techniques and methodologies for quantitative method-related TR are still under construction. Although decades ago Kostoff et al. (2001) took the attitude that "the proper use of automated techniques for text mining is to augment and amplify the capabilities of the expert by providing insights to the database structure and contents, not to replace the experts by a combination of machines and non-experts," and it is still promising for current ST&I studies.

Hybrid TR

It is commonly accepted that, in a hybrid TR model, computer-based techniques help process massive raw data and reduce scalable data dimensions for further manual operations, and expert-based qualitative methods play active roles in result selection and evaluation. Our previous FIP studies kept following this rule where tech mining (e.g. statistical analysis, collaboration and competition analysis) and science overlay mapping (Rafols et al. 2010) techniques were used to capture R&D factors and potential commercial signals, and, at the same time, we set expert engagement as a particular step to run through the whole process, feedback in multiple studying iterations, and help create the FIP mapping (Guo et al. 2012; Robinson et al. 2013a). Furthermore, Huang et al. (2012) enriched the expert knowledge into a detailed workshop setting, and Porter et al. (2013) on the one hand, introduced a semantic map to represent patent applications, and one the other hand, illustrated the attempt that combined quantitative results – identified factors – and expert knowledge to refine the FIP mapping in the workshop process.

Kostoff and Schaller (2001), exploring the combination of qualitative and quantitative methodologies, aggregated TR variants into two fundamental TR approaches: expert-based and computer-based, and then, proposed a disruptive TR developing process which introduced the text mining component of Literature-Related Discovery (LRD) to identify technical disciplines and experts and assisted these experts in workshops (Kostoff et al. 2004). Further, the LRD method (Kostoff et al. 2008) has become an effective instrument to link two or more literature concepts that have heretofore not been linked, and is used to assist medical experts to explore potential treatments of quite a few diseases (Kostoff 2014; Kostoff and Patel 2015), and it does not link with TR at this moment but it would be reasonable to imagine their potential relationships.

Since the lack of high intelligent computer-based techniques, as we mentioned, the hybrid TR that blends qualitative and quantitative methodologies is still a trend in terms of ST&I studies. Yoon and Park (2005) simply used keywords to help expert-based morphology analysis, then, Lee et al. (2009a) introduced citation-based patent analytic approaches and Pajek to identify the relationships between the keywords, which also packaged as keyword-based patent/knowledge map (Yoon and Park 2005; Lee et al. 2009b), and Geum et al. (2015) used co-occurrence analysis to extend the relationship calculation to a two-layer mapping. Another interesting study is that Choi and Park (2009) proposed a citation-based algorithm to link isolated patents as development pathways which solved the relation identification problem to a certain extent, and experts were invited to select key patents and label clusters.

Methodology

Our methodology, as discussed in Related Works, lies mostly under the framework of hybrid TR. We take up the challenge to seek a suitable balance between qualitative and quantitative methodologies, engage ST&I factors for CTI concerns, and develop a strategy and target-driven TR composing method that includes a Term/Topic-based TR Composing Mode, a P&S Pattern-based TR Composing Model, and a Fuzzy Set-based TR Composing Model. The framework of this paper is given in Figure 1.

ST&I textual data is the main input of our method. General ST&I data includes academic publications, patents, academic program proposals, technical product reports, etc. We mainly focus on the textual content of title and abstract, but other sections, e.g. claims of patent data or full text, also make sense for our scope. We apply a Term Clumping process (Zhang et al. 2014a) to clean, consolidate, and cluster the meaningful terms and phrases retrieved by Natural Language Processing, and the outputs – core terms and topics – are considered as the basic elements of our TR models.
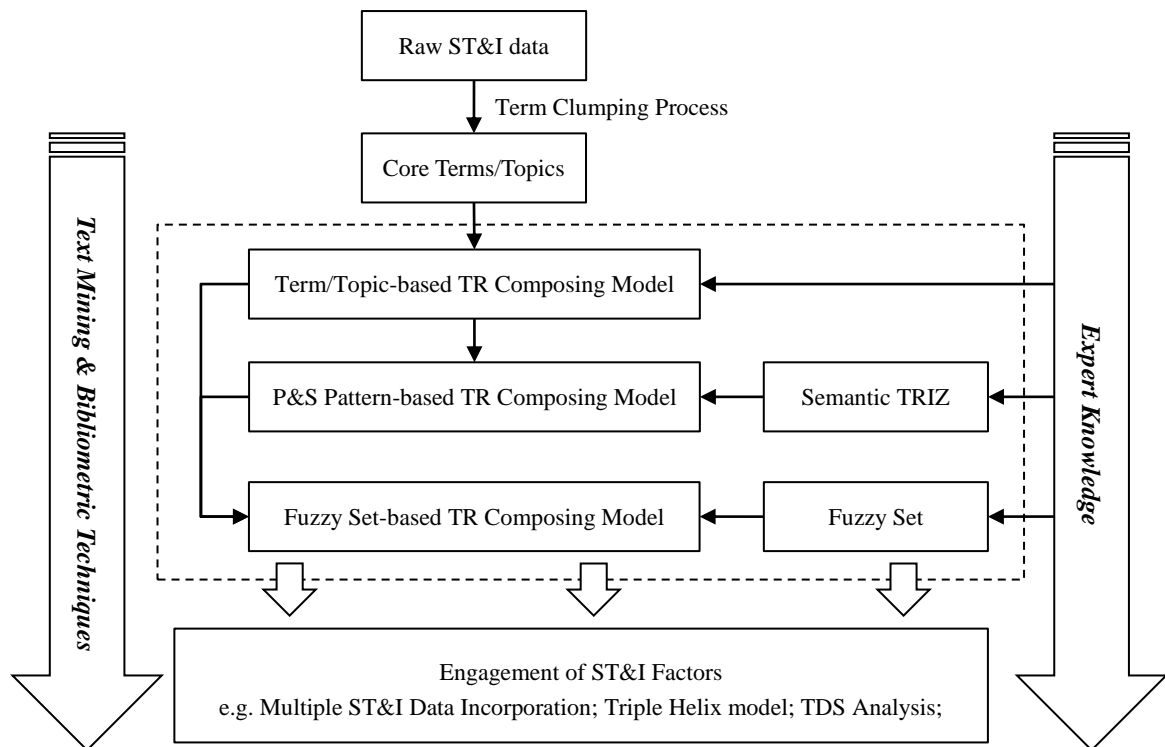
Raw ST&I data

Term Clumping Process

Core Terms/Topics

Text Mining & Bibliometric Techniques

Term/Topic-based TR Composing Model

P&S Pattern-based TR Composing Model ← Semantic TRIZ

Fuzzy Set-based TR Composing Model ← Fuzzy Set

Expert Knowledge

Engagement of ST&I Factors
e.g. Multiple ST&I Data Incorporation; Triple Helix model; TDS Analysis;

Figure 1 Framework of Technology Roadmapping for Competitive Technical Intelligence

Definitions of TR

Aiding with text mining and bibliometric techniques to explore value-added technological information, our TRs mainly emphasize detailed technological evolution of specified NESTs but also give attention to ST&I factors on national R&D level and industrial level. Considering general format of TR, we define the basic element of TR as Object and denote an Object as *O(L, I, T)* where *L* is for Label, *I* is for Implication, and *T* is for Time. The Relationship between objects is described as $R(O_i, O_j)$. The detailed definitions are listed as below:

- Object – the element that is laid out on TR and is usually described as core technological component;

- Label – the semantic structure of Object that would be a term or a phrase or a sentence;

- Implication – the description of TR's strategy and target foci, e.g. technology development and technology commercialization;

- Time – the time that Object appeared firstly in target ST&I data or firstly ascended in top N high-frequency list and usually would be yearly, semi-yearly, or monthly;

- Relationship – the direct or indirect linkage between Objects, e.g. co-occurrence, semantic similarity, problem and solution, collaboration and competition between target organizations.

We have designed a general format of TR shown as Figure 2, where the horizontal axis and vertical axis denote Time and Implication respectively and compose TR's basic framework. We could divide Implication into several phases to indicate a hierarchical structure for specified strategy or target, and we also use a milestone line to highlight a significant event in the past. In particular, we extend the horizontal axis and add a Forecasting section to compare with profiled historical pathways. We also use diverse shapes to distinguish the Object's emphasis for ST&I factors, e.g. different data sources or different organizations. The linkage between Objects is used to reflect the relationships identified by specified association rules.
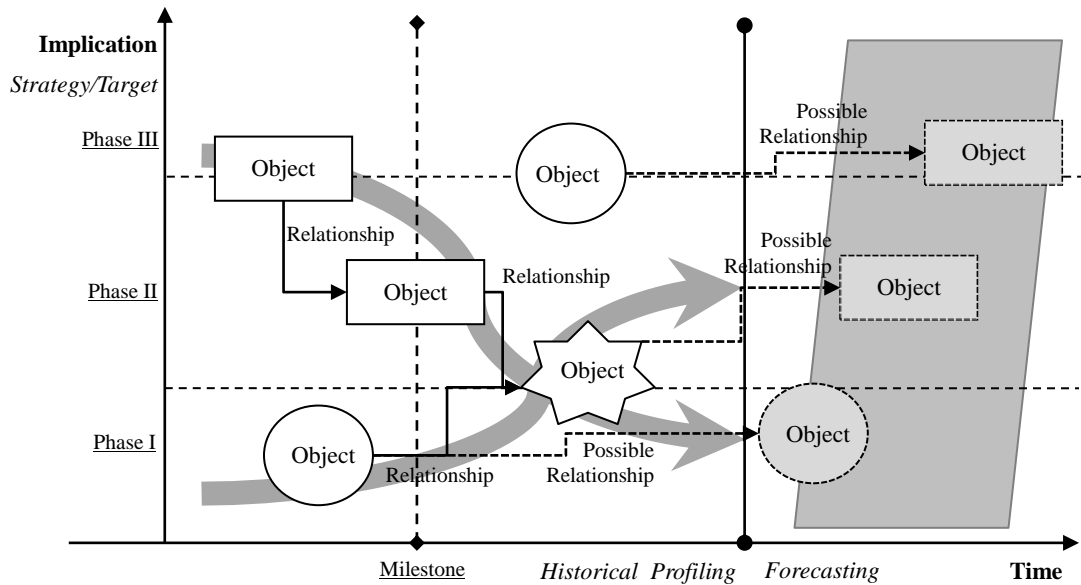
Figure 2 General Format of Technology Roadmapping

Composing Model of TR

Following the definitions and the structure of the general format of TR in Figure 2, we propose three TR composing models with different approaches to identify Object, Relationship, and Implication. The three models are term/topic-based TR composing mode, P&S pattern-based TR composing mode, and fuzzy set-based TR composing model.

1) Term/Topic-based TR Composing Model

The term/topic-based TR composing model is the basic model in our method. We identify the core terms and topics as Objects, and introduce co-occurrence analysis to explore the relationships between Objects. However, this kind of relationship is rough and uncertain, so we do not use the linkage to connect Objects but locate related Objects on a similar layer and group them together. At the same time, we engage expert knowledge to guarantee the results, although quantitative methods are our main tools in this process.

The core terms and topics derived from the Term Clumping process are defined as core technological components in this model, which mostly relate to the detail of target NESTs – e.g. materials, techniques, processing methods, products. This model generally emphasizes the question "What the hot technological components were, are, and will be," which highlights these isolated components and attempts to summarize evolutionary pathways via tracking the changes of their contents.

2) P&S Pattern-based TR Composing Model

Narrowing our focus into specified technological component, we introduce SAO analysis and the Contradiction Matrix concept of TRIZ theory to enrich the core terms and topics into SAO structures, and identify SAO structures as technical problems or related solutions. This paper mostly follows our proposed methodology for SAO structure retrieval and P&S pattern identification (Zhang et al. 2014b). The framework of the P&S pattern-based TR composing model is shown as Figure 3.

In the SAO analysis, we define the core terms and topics as Subject/Object, retrieve their nearby verbs from a combined Title + Abstract field or full text, and define the verbs as Action and the entire phrase as SAO structure. The main concept of the Contradiction Matrix is that external or internal contradictions exist between "object" and "tool", and the way where we solve contradictions is the same as where we find "ideal final result" (Rantanen and Domb 2010). We apply this idea to SAO structures and introduce expert knowledge to help define them as Problems or Solutions. The P&S patterns make good sense to identify the relationships between Problem & Solution, Problem & Problem (P&P), Solution & Solution (S&S), and Solution & Problem (S&P). Zhang et al. (2014b) listed a general definition of the relationship between P&S patterns: P&P – Relate, P&S – Solve, S&S

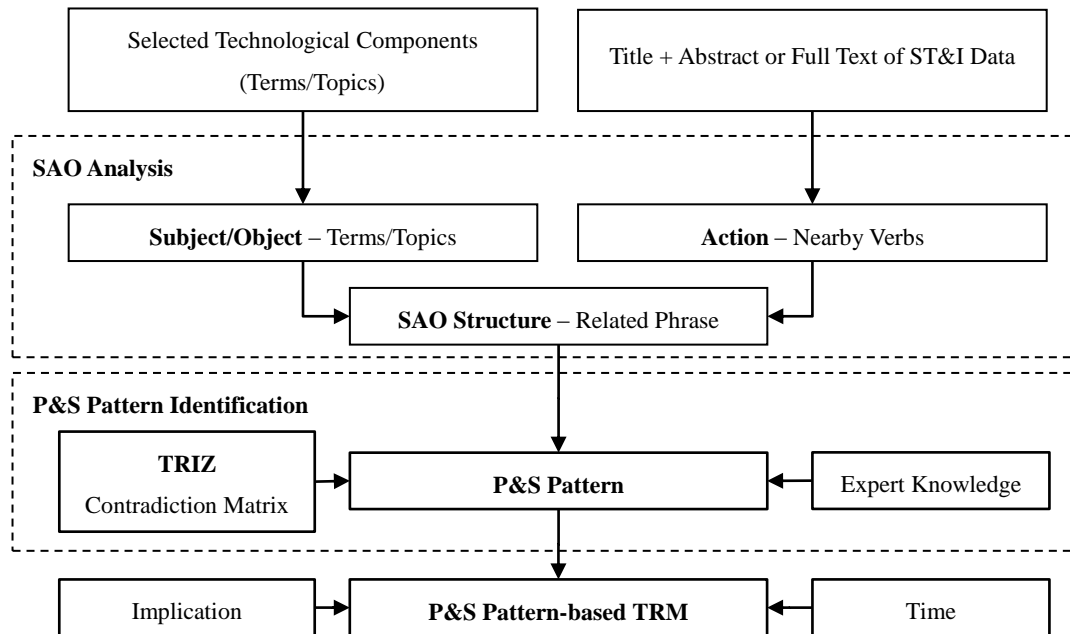– Relate/Upgrade, and S&P – Evolve. We would re-define these relationships depending on real requirements.

Figure 3 Framework of P&S Pattern-based TR Composing Model

The P&S pattern-based TR composing model focuses on the questions "Which problems are addressed, and when?" and "How was the problem solved (new techniques, materials, or something else), and when?" Comparing with the term/topic-based TR, this model helps discover linguistic features of technological components and emphasizes the logical relationships during the process of technology evolution.

3) Fuzzy Set-based TR Composing Model

The fuzzy set-based TR composing model could be considered as an assistant instrument for the above two models. It is easy to define the Time as the coordinate figure of the horizontal axis in TR, but the Implication – our strategy and target – usually is vague and difficult to be defined as exact numeric values. Therefore, in the above two models we draw the TRs manually to adapt the vagueness and uncertainty. Aiming to minimize the aid of manual operations and maximize the usage of expert knowledge in limited time and scope, this model introduces the fuzzy set to transfer vague human thoughts (e.g. expert knowledge) to defined numeric values and helps generate TR automatically.

We denote "all Objects" as the universe $X = \{x_1, x_2, \dots, x_i, \dots, x_{n-1}, x_n\}$ and "each phase of the Implication" as a fuzzy set A_j defined on the X where $j \in [1, m]$. The membership function $A_j(x_i)$ is considered as the degree that Object x_i belongs to the phase A_j, and will be decided depending on research purposes and empirical data.

Engagement of ST&I Factors

Aiming to afford flexibility to address real-worlds concerns for diverse targets and emphases in ST&I analysis, we provide possible approaches to engage ST&I factors in our TR models.

1) Triple Helix Model/ GUISPs Model

The Triple Helix model holds interests on the research knowledge transfer among university, industry, and government (Etzkowitz and Leydesdorff 1995; Etzkowitz and Leydesdorff 2000), and it is also a feasible instrument to measure ST&I activities in many domains (Park et al. 2005). Similarly, the GUISPs model has eyes on R&D strategies and emphasizes the knowledge integration through company partnerships with government agencies, universities, and other industry players (Robinson 2009). Considering the general format of TR in Figure 2, we reserve an interface to describe the information of Triple Helix model/GUISPs model – the shape of Object.

It is easy to retrieve Object's organization information via text mining techniques, and then, we are able to extend the definition of Object *O(L, I, T)* to *O(L, I, T, Org.)* where *Org.* is the organization that Object belongs to. In this context, our TR models describe the fourth dimensional information of Object via its shape, and indicate the interactions according to the Relationships between Objects with the same or different shapes.

2) Multiple ST&I Data Types

There are a bunch of common senses on current ST&I data sources and their emphases. Zhang et al. (2015) summarized popular ST&I data in current researches and classified their emphases into four levels − Idea/Concept, Basic Research, Application Research, and Commercial Information. It is also critical sometimes to combine those emphasis and type-differed ST&I data together, e.g. the time gap between idea and commercialization, and the patent barriers with more commercial and legal issues rather than technical information (Zhang et al. 2013; Zhang et al. 2015).

At this stage, we also provide the possibility to describe multiple ST&I data into our TRs. We extend the definition of Object *O(L, I, T)* to *O(L, I, T, D)* where *D* is used to describe data type and match with the shape of Object. We can imagine the benefit of this kind of combination as the multiple ST&I data-oriented TR opens a window to compare ST&I activities of target technology on different levels and scopes, but we strongly suggest to notice and discuss the diverse emphases of different ST&I data types.

3) Technology Delivery System

TR is developed to trigger change, whether internally in an organization or to create changes to industries and value chains. For the latter, we apply what we call a TDS, which depicts a value chain as a system diagram of components that come together to form a functioning value chain. Below is an example for lab-on-a-chip technology (shown as Figure 4).

Society at large
Interest: health concerns; acceptance of testing
Problem: food & drug safety
Resources: selection power

Patient groups
Interest: better treatment
Problem: visibility, no power to steer research
Resources: very limited

Ministry of Health
Interest: healthcare regulation
Problem: adequate policy development
Resources: public redistribution

Ministry of Economic Affairs
Interest: strengthen knowledge economy
Problem: funding opportunities
Resources: public redistribution, gas money

Insurance companies
Interest: cheaper healthcare
Problem: keeping healthcare affordable
Resources: assumed powerful

Biologists (developers/users)
Interest: seek for possibility for single-cell experimentation; cellomics
Problem: scientific hurdles
Resources: funding

Synthetic chemists (developers/users)
Interest: seek for possibility for high accuracy reactions
Problem: scientific hurdles
Resources: funding

Instrument manufacturers
Interest: Improving laboratory equipment and introducing PoC
Problem: market needs
Resources: considerable

Start-ups
Interest: Niche development using scientific results
Problem: funding, visibility
Resources: limited

multidisciplinary LoC science community

Analytical chemists (developers/users)
Interest: performing novel, better and quicker analysis
Problem: scientific hurdles
Resources: funding

Networks (like Licom in Germany)
Interest: together we can speed up the development and do more
Problem: keeping relevance; creating visibility
Resources: knowledge flows

Electronic engineers (developers)
Interest: providing service as enabler
Problem: scientific hurdles
Resources: funding

Material scientists (developers)
Interest: providing service as enabler
Problem: scientific hurdles
Resources: funding

Pharmaceutical industry
Interest: improved throughput for drug discovery; genomics; proteomics
Problem: seeking methods to improve throughput
Resources: assumed powerful

Hospitals
Interest: speed of analysis, point-of-care
Problem: only limited available, resistance from the central labs
Resources: considerable

Environment (food, environmental and forensic applications)
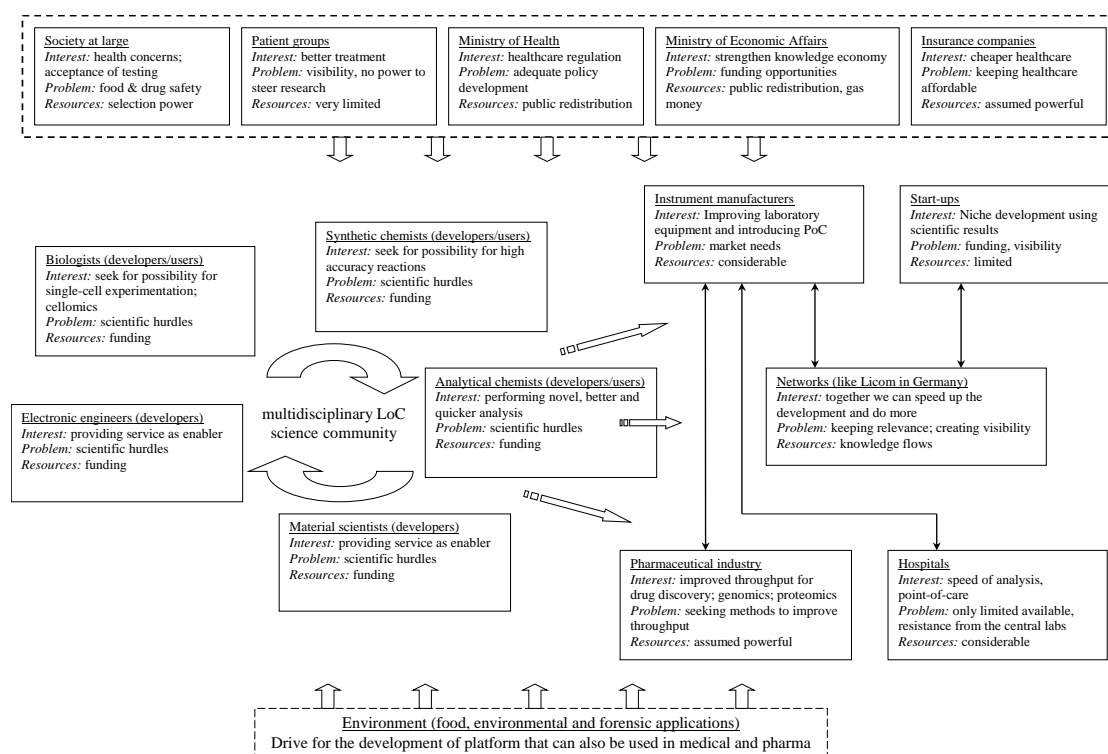Drive for the development of platform that can also be used in medical and pharma

Figure 4 A TDS for the emerging lab-on-a-chip field (Robinson and Boon 2014)

In this example, the multi-disciplinary science community interacts in various ways to create the knowledge that forms a knowledge reservoir that is a source for innovation (central/left-hand side of the diagram). This knowledge can be mapped using tech mining tools (Porter and Cunningham 2004). Industrial actors can be identified, and here they are instrument manufacturers and the pharmaceutical industry. These represent the firms which up value the knowledge from the reservoir, through developing manufacturing techniques and standards. However, the situation is more complex, there are

start-ups involved and hospitals as both co-developers and users of the innovations coming from lab-on-a-chip roadmaps, and thus the value chain is more extended. In addition there are other sectoral/application drivers (bottom of the diagram) which create expectations and hype, which may trigger further "fishing" in the knowledge reservoir, or indeed trigger knowledge production there. Another part of the TDS is the framing conditions, funding agencies, insurance companies (if they are relevant for the value chain) organized user groups which drive demand (here it is patient groups) and regulatory agencies.

The TDS can be used both as a way of depicting the elements and relationships in the situation today as well as a way of mobilising the insights from technology roadmapping to help depict "a future working world", or put another way, the desired future value chain. In this way, it is much more than a picture of boxes and arrows, but it is a translation tool of the roadmapping procedure to those not involved in the roadmapping. Put in another way, the TDS helps inform, justify and evaluate the implementation of TRs.

Empirical Study

In this section, we applied our method to the ST&I data of Dye Sensitized Solar Cells (DSSCs) domain: 1) we blended the term/topic-based TR with the fuzzy set-based TR on Web of Science (WoS) publication data, and automatically generated one TR of global DSSCs development which emphasized the detailed technological components of DSSCs, e.g. materials, techniques, components, and products. 2) We addressed the potential collaboration and competition among government, university, and institution to the P&S pattern-based TR with Derwent Innovation Index (DII) patent data, which hold powerful capability to illustrate the solving pathways of specified technological problems and also indicate the relationships between related organizations.

Global DSSCs TR

Publication data focuses on basic technological components and acts as the first step to transfer innovative ideas to applications (Zhang et al. 2015), thus, aiming to landscape the global DSSCs technological development pathways, we select DSSCs-related scientific publications in WoS. Since DSSCs were invented in 1991 and are still dominating Solar Cell-related techniques, we updated our DSSCs database and captured 13,066 records from 1991 to 2014, and the Term Clumping process (Zhang et al. 2014a) then helped us to retrieve 447 core terms from a raw 191,186-term list.

Consulting with domain experts, we decided to build up three fuzzy sets for material, technique & component, and product to indicate the degree of technology development. At the same time, we evaluated the feasibility of introducing machine learning technique to train the membership functions of the three fuzzy set. It is definite that machine learning technique matched well on our scope, but the difficulty on training an algorithm to understand complex linguistic and technological relationships would extraordinarily increase the uncertainty of our results. In this context, based on expert knowledge, we let the power set $F(X) = \{A_1, A_2, A_3\}$, and choose Gaussian distribution to identify the membership functions as below.

$$A_1(x): X \sim N\left(0, \frac{1}{2\pi}\right), x \in [0,1]$$
$$A_2(x): X \sim N\left(\frac{1}{2}, \frac{1}{2\pi}\right), x \in [0,1]$$
$$A_3(x): X \sim N\left(1, \frac{1}{2\pi}\right), x \in [0,1]$$

We firstly convened experts to classify the 447 terms into one of the three fuzzy sets and marked a membership grade $A_j(x)$ for the selected fuzzy set A_j. It is promising to understand that one term would indicate both material and technique or both technique and product, and experts help enforce one category but fuzzy set reflects the degree of this kind of belonging. As an example, because of diverse background and relevant, some experts categorized the term "electron injection" as technique & component and marked the membership grade as 0.95, while some other experts marked as 0.6 to the fuzzy set – material because they thought it related to material more but was not an total material. We then used the membership function conversely to calculate the x value which was identified as the degree of technology development. Furthermore, the mean of the x values derived from different experts was set as the Object's Y value on the mapping while its X value was the first year when it appeared in the dataset.

The term/topic and fuzzy set-based TR for global DSSCs development is given in Figure 5 (from 1991 to 2002) and Figure 6 (from 2003 to 2014). It is obvious that this mapping explores the detailed DSSCs technologies during its past 24-year development pathway, but professional expertise would be necessary to understand its insights. Aiding with domain experts, we address several concerns as below:

1) The preparation material of DSSCs was always a hot topic for researchers. The first peak time was from 1996 to 2000, when nanotechnology was introduced to prepare electrode and electrolyte in 1998, and then, the second peak time came with the invention of graphene in 2004 which firstly appeared in our list as graphene film four years later. The combination of these two emerging technologies captured the interests of researchers in the following years. TiO2 and ZnO are still the leading materials for DSSCs, and since 2010 various kinds of materials have been applied as composite or mix materials.

2) The device durability and low-cost fabrication were two main problems during the first 15 years of DSSCs' development, but environment-friendly feature has become a popular and emergent requirement since the term "environmental purification" firstly appeared in 2012. In parallel, more and more one-step or two-step had being used to name related techniques and methods since 2009, which seemed to indicate the needs for rapid and convenient DSSCs fabrication.

3) DSSCs-related techniques concentrated on solar cell rather than other industrial applications, but drug delivery and biomedical appeared in 2009 and 2011 respectively which would be a good starting point for extended applications of DSSCs. Although experts explained this phenomenon was due to the policy restrictions in most European countries and Japan, note here one argument for rare applications in our results is that we would likely over-clean the records and terms before 2011.

4) Dye is the highest frequent term on the mapping and there is no doubt that it is the most important sub-technology in DSSCs. Organic dye and metal complex dye were two leading directions until 2014 where researchers attempted to broaden the selection of organic or metal substances.
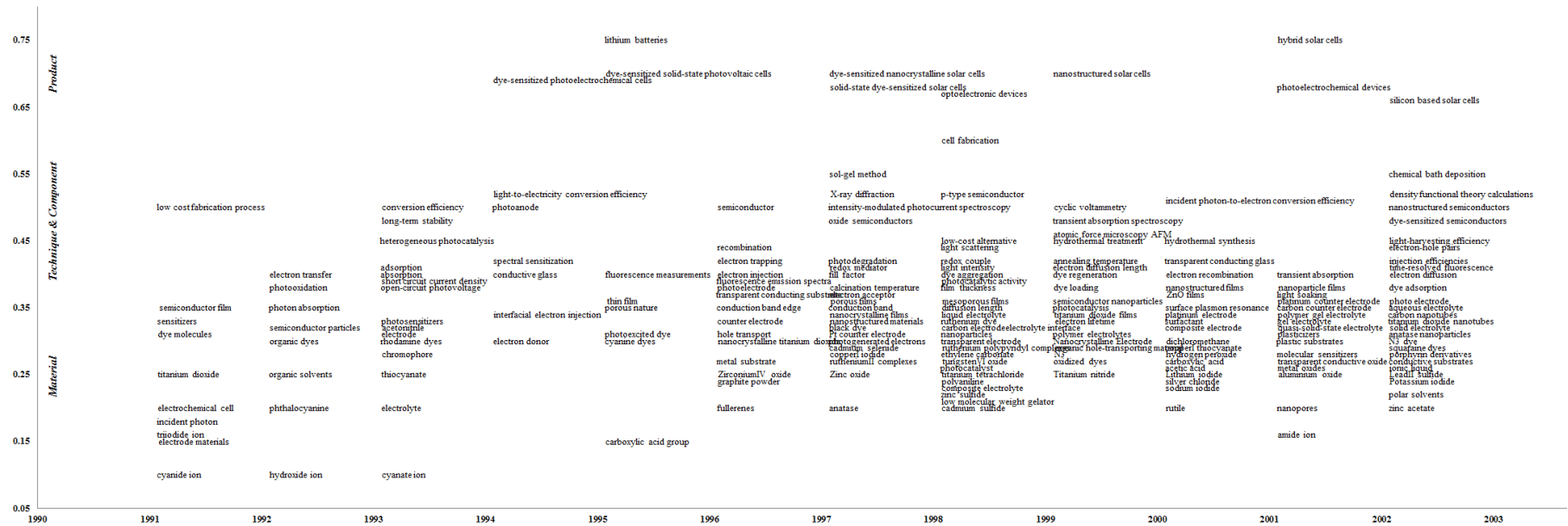
Figure 5 Term/Topic and Fuzzy Set-based TR for Global DSSCs Development (from 1991 to 2002)
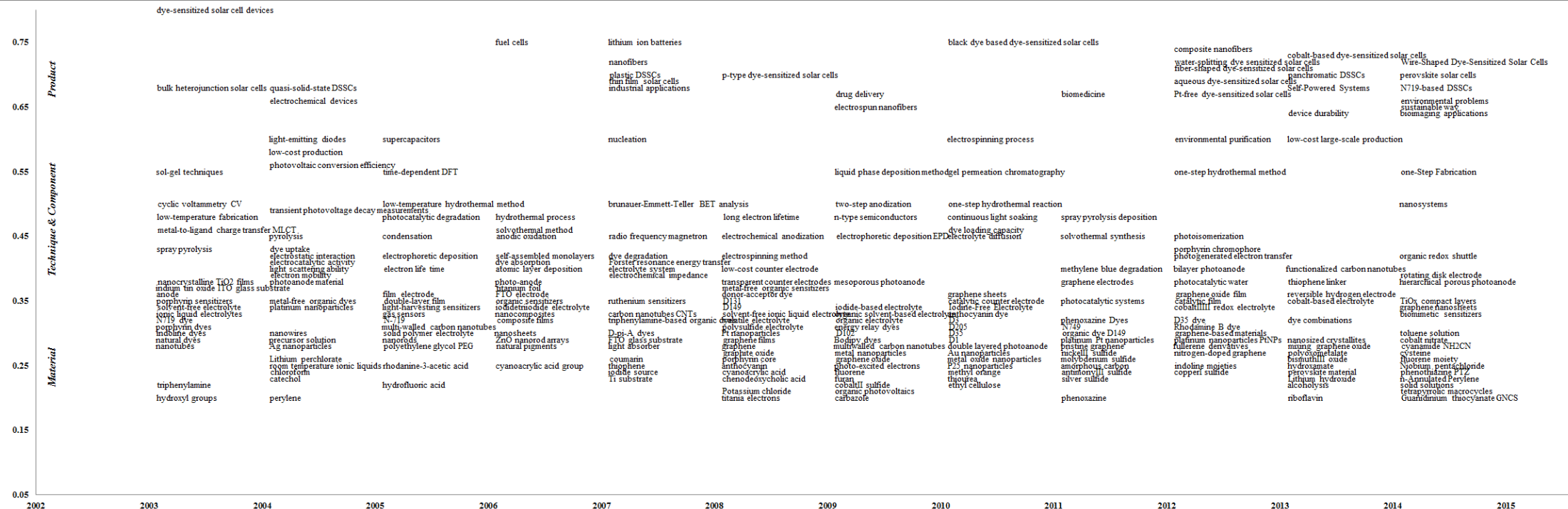
Figure 6 Term/Topic and Fuzzy Set-based TR for Global DSSCs Development (from 2003 to 2014)

P&S Pattern-based TR for Triple Helix Model of China's DSSCs Development on Conversion Efficiency

Universities and institutions are the leading role in publications, while governments and companies hold more interests to patents due to their commercial concerns, which would lead to the success on dominating global or industrial competitions. Therefore, we choose the DII patent data for exploring the Triple Helix relationships among government, university, and company in China's DSSCs industry. Based on our previous experiences, 1) we divided the Academy part of original Triple Helix model into academy and university to distinguish their distributions; 2) we set Chinese Academy Science (CAS) as a special category to highlight this academic institution which has a significant government-supporting background in China; 3) aiming to demonstrate the advantage of the P&S pattern-based TR on tracking problem-solving pathways, we narrowed our focus to the "conversion efficiency" problem, which is considered as one problem throughout the entire development pathway of DSSCs.

Aiding with automatic software, we retrieved 186 SAO structures from the raw content of 1,167 patent records, the priority country of which is China. We then arranged our domain experts to evaluate these SAO structures and identify 74 solutions and their relationships. We ignored the Object's shape for a clearer graph and marked the Triple Helix category as the initial letter: University – U, Academy (Institution) – A, Government – G, Industry – I. We presented our results in Figure 7. This TR drew a clear landscape to understand how the conversion efficiency problem was solved in China and how the key players of China's DSSCs industry played with their interested techniques, and helped explore the potential collaboration and competition relationships in the Triple Helix model. Our discoveries are listed as below:

1) In China, the "conversion efficiency" problem was solved in four directions – a) to absorb more light via enlarging surface area, adding more layers, and etc.; b) to improve the efficiency of the dye, where organic materials and metals were the two foci; c) to improve the efficiency of the film, anode, or electrode, where TiO_2 and ZnO were two basic materials, nano materials were widely used, and graphene was becoming a popular one; d) to transfer the state of the electrolyte from liquid to gel and solid.

2) The "measurement of conversion efficiency" was the direct related problem, while we were also able to identify "electrolyte leaking", "device stability" and "photoelectron transport loss" as relevant problems. Actually, a reasonable understanding is sometimes one patent would likely focus other problems and the "conversion efficiency" problem was solved the same as the focused one.

3) The University group was the main force of China's DSSC researches, which provided 53 solutions in the past 10 years. The CAS followed with 10 solutions, while the Industry group had 9 and the Academy had 2. Resulting from Figure 6 and experts' experiences during the evaluation process, we take the attitude that the patents of China's University hold more innovative techniques than other organizations and the Industry paid more attention to the preparation methods.

4) China's government is considered as the most powerful driving force for China's DSSCs development. On the one hand, CAS, the leading organization with the largest number of solutions on the mapping, definitely contributed excellent works for solving the "conversion efficiency" problems. Its government background and the massive program and funding supports obtained from government make us believe that China's government was highly involved into DSSCs industry. On the other hand, compared our analytic results for the data before 2012 (Zhang et al. 2014c), in 2014 the Government finally directly appeared in China's DSSCs patents for conversion efficiency problem. We traced this patent and noticed that it was applied by National Center for Nanoscience and Technology, China, an academic research centre built by CAS and the Ministry of Education, China (that is the reason we only marked it as A/G on the mapping). Nevertheless, we are able to foresee that more and more state-owned enterprises or institutions would join in this army to support China's DSSCs development.

5) The collaborations between the Triple Helix organizations in China are rare. Only 2 solutions were provided by collaborations between the University and the Industry – University of Fudan with Changzhou Youze technology Co. Ltd., and Dalian University of Technology with Yingkou Opvtech Energy Co. Ltd. It is obvious that geo-advantage played an important role in both collaborations.
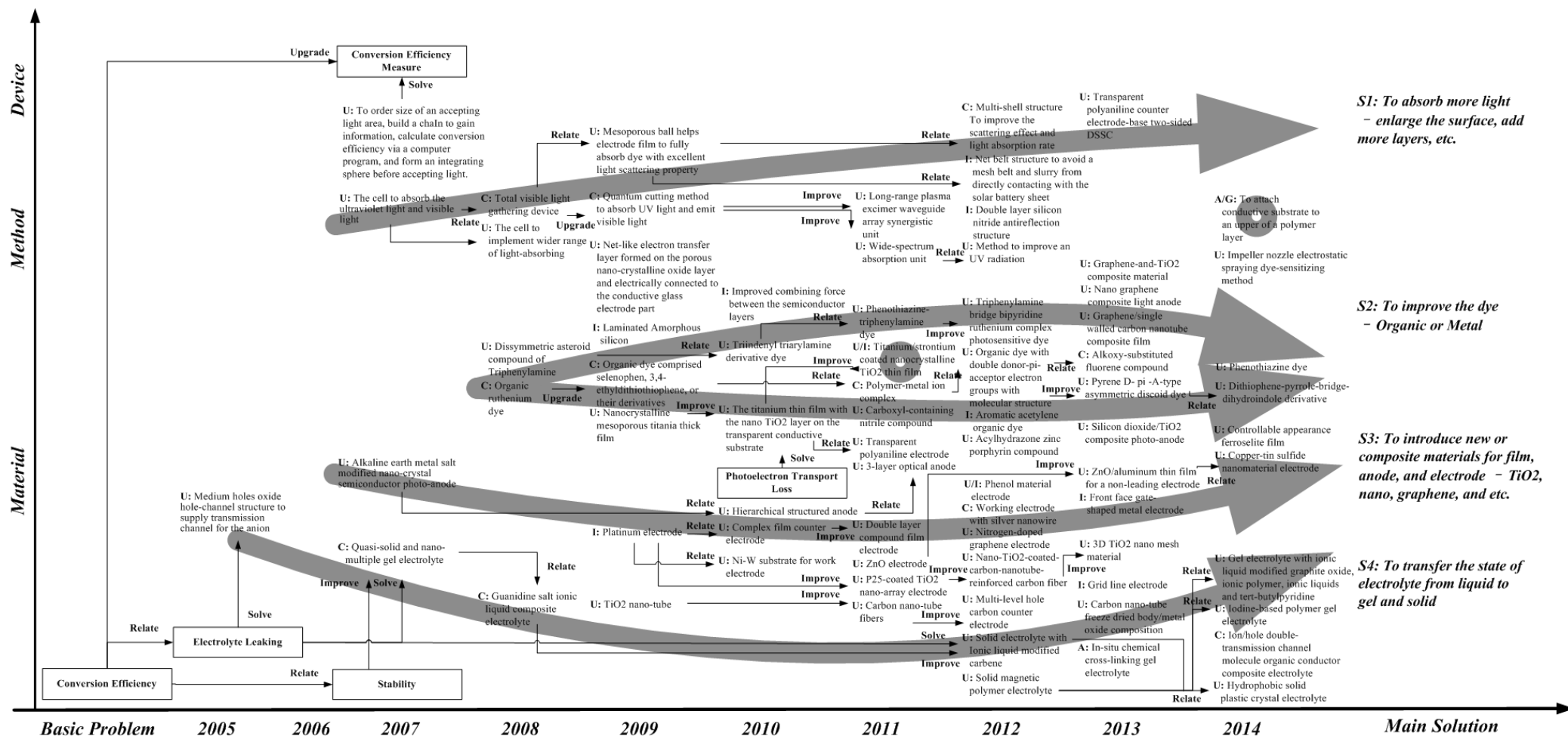
Device

Method

Material

Upgrade

Conversion Efficiency Measure

Solve

U: To order size of an accepting light area, build a chaIn to gain information, calculate conversion efficiency via a computer program, and form an integrating sphere before accepting light.

Relate

U: Mesoporous ball helps electrode film to fully absorb dye with excellent light scattering property

C: Multi-shell structure To improve the scattering effect and light absorption rate

Relate

U: Transparent polyaniline counter electrode-base two-sided DSSC

S1: To absorb more light – enlarge the surface, add more layers, etc.

Relate

I: Net belt structure to avoid a mesh belt and slurry from directly contacting with the solar battery sheet

U: The cell to absorb the ultraviolet light and visible light

Relate

C: Total visible light gathering device

Upgrade

C: The cell to implement wider range of light-absorbing

C: Quantum cutting method to absorb UV light and emit visible light

Improve

Improve

U: Long-range plasma excimer waveguide array synergistic unit

I: Double layer silicon nitride antireflection structure

A/G: To attach conductive substrate to an upper of a polymer layer

U: Net-like electron transfer layer formed on the porous nano-crystalline oxide layer and electrically connected to the conductive glass electrode part

U: Wide-spectrum absorption unit

Relate

U: Method to improve an UV radiation

U: Impeller nozzle electrostatic spraying dye-sensitizing method

I: Improved combining force between the semiconductor layers

U: Phenothiazine-triphenylamine dye

Relate

U: Triphenylamine bridge bipyridine ruthenium complex photosensitive dye

U: Graphene-and-TiO2 composite material

U: Nano graphene composite light anode

S2: To improve the dye – Organic or Metal

I: Laminated Amorphous silicon

U: Dissymmetric asteroid compound of Triphenylamine

C: Organic ruthenium dye

Relate

U: Triindenyl triarylamine derivative dye

Improve

U/I: Titanium/strontium coated nanocrystalline TiO2 thin film

U: Graphene/single walled carbon nanotube composite film

C: Organic dye comprised selenophen, 3,4-ethyldithiothiophene, or their derivatives

Relate

Relate

U: Polymer-metal ion complex

Relate

U: Organic dye with double donor-pi-acceptor electron groups with molecular structure

C: Alkoxy-substituted fluorene compound

U: Pyrene D- pi -A-type asymmetric discoid dye

Relate

U: Phenothiazine dye

Upgrade

Improve

U: Nanocrystalline mesoporous titania thick film

U: The titanium thin film with the nano TiO2 layer on the transparent conductive substrate

U: Carboxyl-containing nitrile compound

I: Aromatic acetylene organic dye

U: Acylhydrazone zinc porphyrin compound

U: Silicon dioxide/TiO2 composite photo-anode

Improve

U: Dithiophene-pyrrole-bridge-dihydroindole derivative

Relate

U: Controllable appearance ferroselite film

U: Copper-tin sulfide nanomaterial electrode

S3: To introduce new or composite materials for film, anode, and electrode – TiO2, nano, graphene, and etc.

U: Alkaline earth metal salt modified nano-crystal semiconductor photo-anode

Solve

U: Transparent polyaniline electrode

U: 3-layer optical anode

U: ZnO/aluminum thin film for a non-leading electrode

Photoelectron Transport Loss

Relate

U: Hierarchical structured anode

Relate

U/I: Phenol material electrode

I: Front face gate-shaped metal electrode

Relate

U: Medium holes oxide hole-channel structure to supply transmission channel for the anion

I: Platinum electrode

Relate

U: Complex film counter electrode

Improve

U: Double layer compound film electrode

C: Working electrode with silver nanowire

C: Quasi-solid and nano-multiple gel electrolyte

Relate

U: Nitrogen-doped graphene electrode

U: 3D TiO2 nano mesh material

Improve

Solve

Relate

U: Ni-W substrate for work electrode

U: ZnO electrode

Improve

U: Nano-TiO2-coated-carbon-nanotube-reinforced carbon fiber

I: Grid line electrode

U: Gel electrolyte with ionic liquid modified graphite oxide, ionic polymer, ionic liquids and tert-butylpyridine

S4: To transfer the state of electrolyte from liquid to gel and solid

Relate

C: Guanidine salt ionic liquid composite electrolyte

U: P25-coated TiO2 nano-array electrode

Improve

U: Carbon nano-tube freeze dried body/metal oxide composition

Relate

U: Iodine-based polymer gel electrolyte

U: TiO2 nano-tube

U: Multi-level hole carbon counter electrode

Improve

Relate

Relate

Electrolyte Leaking

Solve

U: Carbon nano-tube fibers

U: Solid electrolyte with Ionic liquid modified carbene

A: In-situ chemical cross-linking gel electrolyte

C: Ion/hole double-transmission channel molecule organic conductor composite electrolyte

Relate

Conversion Efficiency

Relate

Stability

Improve

U: Solid magnetic polymer electrolyte

Relate

U: Hydrophobic solid plastic crystal electrolyte

Basic Problem   2005   2006   2007   2008   2009   2010   2011   2012   2013   2014   **Main Solution**

Figure 7 P&S Pattern-based TR for Triple Helix Model of China's DSSCs Development on Conversion Efficiency (from 2005 to 2014)

Discussion

Referring to our TR composing models and the results obtained in the empirical study, we summarize the criteria for TR model selection and evaluation and discuss the similarity and difference between TR and other foresight projects in this section.

Criteria and Metrics

How to choose the best TR model for specified requirements and evaluate the efficacy of TR is one of the main research questions in this paper. Actually one possible answer of this question would likely relate to the balance between qualitative and quantitative methodologies. Researchers always argue the subjective bias of expert knowledge and the uncertainty of data evidence, but the both heavily influences the implementation of TR including selection and evaluation.

1) Criteria for Expert Engagement

We engage experts in various kinds of ways, e.g. questionnaire, interview, seminar, and workshop, and there are two criteria that we need to take consideration – background relevant and cost (including time and expense). The ideal situation is the background of expert is highly relevant and the cost is low, however, experts usually are busy, expensive, and might not match your need exactly. At this stage, in Table 1 we summarize the criteria for expert engagement in possible situations.

Table 1 Criterion for Expert Engagement

Level	Criterion	Situation
A	Ideal Situation – to engage expert knowledge as much as you can;	• High Relevant and Low Cost;
B	Good Situation – to emphasize expert knowledge aiding with limited quantitative methods;	• High Relevant and Normal Cost; • Normal Relevant and Low Cost; • Normal Relevant and Normal Cost;
C	Normal Situation – to strict expert knowledge in limited scopes and prefer quantitative methods;	• High Relevant and High Cost; • Normal Relevant and High Cost;
D	Bad Situation – to apply quantitative methods as much as you can (high intelligent IT techniques might be necessary);	• Low Relevant;

The promise here is that the more experts we have the more creditability we are able to gain, and we prefer expert-based qualitative methodologies rather than machine-based quantitative methodologies. As shown in Table 1, we classify the possible real situations into four types – Ideal, Good, Normal, and Bad. In the Ideal and Good situation, we hold the capability to arrange large-scale expert engagement for our studies, and quantitative methodologies would only act as an assistant tool for expert-based decision making. Mostly these situations occur in the R&D plans of national governments or big business, and they would be time-consuming. The Normal situation is common in institutions and small and medium enterprises, where the resources are limited and it is necessary to take the place of experts via quantitative methodologies. However, a systematic research framework construction and feasibility study are necessary, and appropriate expert engagement would be the guarantee for outputs. We do not suggest persisting in continuing the research in the Bad situation, unless it is possible to introduce high intelligent IT techniques to fully support the study.

Referring to Table 1, it is helpful to think about expert resources and budget before we start a TR study, and know which kind of balance between qualitative and quantitative methodologies is fit for our current situation. That would be the pre-assessment for TR selection and evaluation, since we need to know what is on our hand.

2) Criteria for TR Selection and Evaluation

This section compares our three TR models with qualitative method-based TRs, quantitative method-based TRs, and hybrid TRs in Emphasis, Situation Requirement, Data Quality, Flexibility (e.g. combining with ST&I factors, implementing for real-world applications), Visualization, and Understanding (as shown in Table 2). As discussed in the Related Works, the qualitative method-based TRs are mainly based on expert knowledge and might involve limited statistical models for results computation, the quantitative method-based TRs are mostly automatic generated mappings aiding with

text mining, bibliometrics, and other intelligent techniques, and there is rare or very little expert engagement for them, while the hybrid TRs combine them both to a certain extent. We lay out as more as possible factors that influence the efficacy of TR, and propose the criteria for TR selection and evaluation as below:

The qualitative method-based TRs hold high flexibility while designing and implementation, and even do not need data support. Their visualization efficacy highly depends on real needs, which sometimes is graph-based but sometimes is text-based. The visual approach would also influence the difficulty on understanding, although most of them are easy-going for governors, administrators, and the ones with limited expertise. However, the guarantee from expert ensures the credibility of outputs, and the qualitative method-based TRs are still the most popular formats in current implementations.

The quantitative method-based TRs highly depend on related algorithms and data, and are highly intelligence for data analyses and visualization. However, the algorithms sometimes strictly limit the TRs in designed framework and would be not flexible for different data type, graphic format, and etc. Understanding on this kind of TRs would need professional expertise. Nevertheless, possible missing relationships between items on the mapping would lead to misunderstanding. It is also critical to totally believe in a machine in real-world applications.

The hybrid TRs would be a middle way between qualitative method-based TRs and quantitative method-based TRs and obtain the benefits from the both. One challenge of hybrid TRs that we need to concern is to adapt the different requirements and backgrounds of a number of disciplines, e.g. computer science, management, and target technology.

The fuzzy set-based TR, similar with quantitative-based TRs, fixes elements into designed basic graph, prefers high data quality, and is not quite flexible for changing requirements. Its advantage would be the possible adaptability for the Bad situation of Table 1, e.g. only have very little experts or expert backgrounds are low relevant to the target. At this stage, it would likely be promising that fuzzy set collects and transfer the rough and limited knowledge as a group decision;

The term/topic-based TR follows most benefits from hybrid TRs, where the appropriate expert engagement reduces the requirements on data quality and increases the flexibility on real-world applications. However, this model mainly focuses on technological components, and the relationships between technological components are derived from quantitative analyses, which sometimes would be rough and uncertain. The P&S pattern-based TR increases expert engagement to help explore relationships between technological components and its focus on problem-solving pathways also increases the visualization efficacy.

Generally, we need to pay regard to current resources and foci of TR studies, and Table 2 would act as a guidebook that provides feasible criteria for TR selection and evaluation.

Table 2 Criterion for TR Selection and Evaluation

No.	TR Type	Emphasis	Situation Requirement	Data Quality	Flexibility	Visualization	Understanding
1	Term/Topic-based TR	Component and Evolutionary Pathways	Normal Situation or more	Normal	Normal	Normal	Professional
2	P&S Pattern-based TR	Relationships and Evolutionary Pathways (Problem Solving Pathway)	Good Situation	Normal or Low	Normal	Good	Intuitive
3	Fuzzy Set-based TR	Component and Evolutionary Pathways	Possible Bad Situation	Normal	Low	Normal	-
4	Qualitative Method-based TR	Landscape, Evolutionary pathway, or Specified Problem-oriented	Good Situation	N/A	High	Normal	Intuitive
5	Quantitative Method-based TR	Components or Evolutionary Pathways	Bad Situation or more	High	Low	Good	Professional
6	Hybrid TR	Component, Relationship, or Evolutionary Pathways	Normal Situation or more	Normal	Normal	Normal	Intuitive/ Professional

Comparison between TR and Other Foresight Projects

As shown in the general format of TR in Figure 2, we attempt to combine historical data profiling and forecasting studies within TR model, which seems to be an evidence to indicate a high relevant between TR and foresight studies. Based on Table 2, we list the similarity and difference between TR and other foresight projects in Table 3.

Table 3 Comparison between TR and Other Foresight Projects

No.	*Factors*	*TR*	*Expert-based Foresight*	*Quantitative-based Foresight**
1	Future-oriented	One of main foci	Main focus	Main focus
2	Visualization	Mapping-preferred	No special pursuance	No special pursuance, but some prefer
3	Historical Data Profiling	One of main foci, profiling historical data for assessment and forecasting	No special pursuance, but emphasizing the logical relation between the past and future	Recognizing and learning from historical data for prediction
4	ST&I Factor-involved	Concentrating on specified one or two ST&I factors	Involving with ST&I factors as more as possible	Ignoring possible influence from ST&I factors
5	Expert Engagement	To seek suitable balance between quantitative and qualitative methodologies	Emphasize quantitative-based prediction models*, or highly expert-engaged	Almost no expert-required

*The quantitative-based foresight mainly indicates mainstream algorithms and models in artificial intelligence, data mining, and machine learning domains, e.g. link prediction (Liben-Nowell and Kleinberg 2007), burst detection (Bogard and Tiederman 1986), collaborative filtering (Resnick et al. 1994), recommender system (Resnick and Varian 1997), and time series analysis (Hamilton 1994).

Actually current foresight projects are totally divided into two isolated parts: expert-based foresight and quantitative-based foresight. R&D managers prefer qualitative methods for forecasting study, which ensures the creditability and meets the needs from macro level, e.g. national strategy. In contrast, researchers in mathematics and computer science endeavour in machine-based methodologies to predict events or trends in the near future, e.g. energy demand and economy time series, although it still needs a long time to apply these models to solve real-world problems.

It is obvious that TR shares most foci with expert-based foresight projects, e.g. future-oriented, ST&I factor-involved, and expert-required, but the "roadmapping" feature of TR emphasizes the visualization process and historical data profiling. At the same time, since TR models seek to introduce quantitative methodologies to support decision making, one feasible application is to use statistical models of quantitative-based foresight to help expert to foresee possible changes in the future. At this stage, TR seems to be the bridge that connects isolated expert-based foresight and quantitative-based foresight projects.

Conclusions

In this paper, we have presented an approach to TR which builds on a family of techniques both quantitative and qualitative, created a typology of tools and applied them to the case of dye-sensitized solar cells. TR for breakthrough technology fields requires the integration of a number of techniques to be able to handle the complexity of emergence and make it practicable to inform strategy and policy making. Such TR for technology fields can be further developed in a number of ways, by being 1) integrated with expert engagement to anticipate further multi-level evolutions e.g. in Robinson (2009) and 2) included in exploring multiple micro-level pathways such as open-ended roadmapping (Robinson and Propp 2008; Stirling 2008) to determine individual strategies to determine innovation pathways. A key challenge for TR is to evolve as part of ongoing strategy or policy making. This requires "living TR". Our approach presented here allows for regular updating and evaluation as part of

such a "living TR" approach, and our future work will explore further this link to ongoing strategy making.

Acknowledgement

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