Technology Evolution and Technology Forecasting Based on Engineering Big Data

Fuhua Wang
School of Mechanical Engineering
Shanghai Jiao Tong University
Shanghai, China
e-mail: fuhuawanghz@sjtu.edu.cn

Zuhua Jiang
School of Mechanical Engineering
Shanghai Jiao Tong University
Shanghai, China
e-mail: zhjiang@sjtu.edu.cn

Hong Zheng
School of Mechanical Engineering
Shanghai Jiao Tong University
Shanghai, China
e-mail: zhhong@sjtu.edu.cn

Xiaoming Sun
School of Mechanical Engineering
Shanghai Jiao Tong University
Shanghai, China
e-mail: xmsun@sjtu.edu.cn

Haili Wang
School of Mechanical Engineering
Shanghai Jiao Tong University
Shanghai, China
e-mail: hlwang@sjtu.edu.cn

Xinyu Li
School of Mechanical Engineering
Shanghai Jiao Tong University
Shanghai, China
e-mail: lxy2003jacky@sjtu.edu.cn

***Abstract*—Big-data-driven technology innovation management and technology forecasting in engineering design represent a new challenge that we have to cope with. Data mining algorithms, technology evolution methods and technology forecasting models desiderate theoretical breakthroughs and practical innovations. In this paper, the future development trend of technology is forecasted by analyzing engineering big data. The influence of internal and external factors on the evolution path of technology is researched. Hotspots and frontier fields of current technical development are analyzed. Based on technological innovation path and paradigm shift, we explain the mechanism of technology evolution from multiple perspectives, such as individual/group, short-term/long-term, sudden-change/gradual-change. Technology forecasting and results evaluating methods based on the multi-stage evolution mechanism are proposed. The proposal helps enterprises improve their ability to forecast technological development trends of industries, as well as decision ability of technological Research and Development (R&D) innovation.**

Keywords-data mining; technology evolution; technological paradigm shift; technology forecasting.

I. INTRODUCTION

The fierce market competition has prompted enterprises, which are engaged in product Research and Development (R&D) and technology management, to continuously study the entire process of technology evolution. A diversified and forward-looking technology development layout is proposed for R&D, design and manufacture of the next generation products [1]. However, in the face of massive, real-time, multi-source, heterogeneous engineering knowledge creation and technological paradigm shift records, the challenges are how to make technical knowledge managers and design innovators to: in-depth grasp the rules of engineering technology innovation, comprehensively have an insight into development trends of engineering fields, and systematically plan strategies of engineering product innovation [2]. These challenges have been the basic and urgent work of product development and decision-making management.

The rest of the paper is structured as follows. In Section 1, the background and significance of this topic are introduced. In Section 2, related works about technology forecasting are investigated and summarized. In Section 3, a forecasting model of technical evolution is proposed, considering both the technology supply side and the social demand side. Also, technology forecasting framework for engineering big data is proposed. In Section 4, the advantages and disadvantages of the methods mentioned in this paper are summarized, as well as the direction of future work.

II. RELATED WORKS OF TECHNOLOGY FORECASTING

Technology forecasting began with the US Department of Defense in 1950s, aiming at predicting military technology. Technology forecasting is a method that continuously observes and researches current and future development trends of technology, and evaluates the potential and development prospects of the technology in future application fields, then provides decision-makers with in-depth decision support [3]. Previous research has been based on the Technology Road Mapping Model (TRM) [4][5],

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TABLE I. CHARACTERISTICS OF TECHNOLOGY FORECASTING METHODS

Methods	Source	Detailed Methods	Applicability	Efficiency
Technology Roadmapping	Patent texts	Interviews, observations, questionnaires, and statistical analysis	High, for any technology forecasting	Low, require the assistance of customized system
Bibliometrics	Patents and academic journals	analysis of word frequency and citations	High, high data acquisition and availability	High, mature aided software
Information Analysis	Patents and academic journals	analysis of scenario and cycle theory	Medium, affected by data bias	Low, dependent on many experts
Complex Network Analysis	Patents, academic journals and web forums	analysis of co-words, co-citation networks	Medium, affected by available knowledge set	Medium, interpret and verify by expert knowledge

Bibliometrics [6][7], Information Analysis [8], and Complex Network Analysis [9][10].

Most scholars qualitatively developed TRM-based forecasting standards and schemes [11][12], following the first proposed structural TRM model by Phaal et al. [13]. Press, subject category, author, country and keywords of academic journals are mainly analyzed by bibliometrics, especially the common analysis based on word frequency and citation. Sinha [14], Liu et al. [15], Wang et al. [16] have analyzed and explored the long-term development profiles and principles through bibliometrics studies in fields of biology, medicine and environment.

With the promotion and application of patent information analysis, many scholars have performed technology forecasting by information science. Mi [17] forecasts the technological development prospects for the laptop industry using information from the past 10 years by patent information analysis method, in order to provide reasonable decision for the strategic layout of patents.

Complex network analysis has also been used to mine hotspots and track research trends in recent years. This method mainly analyzes key co-words, co-introduction, co-authoring and their relationships in published papers by evaluation indexes of a complex network, to identify frontier topics and forecast technological development trends [18]. This method often combines with traditional methods. For example, Zhang et al. [19] establish a forecasting model of technological topics combined with the TRM and the bibliometrics, based on a complex network. Cheng et al. [20] combine traditional bibliometrics with anomaly testing methods of a network. An anomaly event detection model was proposed to explore the development trends in social computing fields.

The characteristics of the above technology forecasting methods are summarized in Table 1. However, there are some shortcomings in the existing researches because existing technology roadmapping needs to consult a large number of literature works in a specific field and the process is time consuming. Bibliometric measurement and information analysis focus on quantitative descriptions of statistics. Only the "explicit" statistical knowledge can be obtained and it is difficult to identify the potential development trend. Complex network analysis pays much attention to relationships between research variables, and thus it cannot consider particularities of variables. On the other hand, the researches worked by Fye et al. [21] have shown that the accuracy of technology forecasting for short-term (1-5 years) and medium-term (6-10 years) is about 38-39%, while that for long-term (11 years and above) is only 14%. However, there are few studies on “accuracy of technology forecasting”. There are few papers to retrospect and evaluate accuracy for their models of technology forecasting [22]. Most accuracy evaluations of forecasting are for commercial and medical fields. The evaluation system based on engineering/scientific technology is more limited.

Previous studies in this field [23]-[25] only focus on two highly structured data sources: technology patents and journals. Their methods of technology forecasting are limited to qualitative or semi-quantitative research (such as Gartner's Hype Cycle [26]), without considering the inherent mechanism of technology development, such as individual/ group, short-term/ long-term, sudden-change/ gradual-change. Also, these works seldom consider the impact of external social environment and internal user needs on technological paradigm shift. As a result, the accuracy and reliability of existing models are insufficient. Therefore, in big data environment, we propose a novel forecasting model of technological development trend, which considers both external market demand and internal technology evolution law. In addition, we propose an algorithm framework of technology forecasting based on "Technical Knowledge Evolution-Technological Paradigm Transition-Technological System Revolution". It integrates Natural Language Processing (NLP), semantic network analysis, text meta-analysis, and deep learning algorithm into the framework. The proposal improves accuracy and validity of forecasting results and provides new ideas for the research in this field.

III. FRAMEWORK OF TECHNOLOGY FORECASTING BASED ON ENGINEERING BIG-DATA

A. Data mining and semantic analysis for massive multi-source heterogeneous big-data in product development and engineering design

Driven by product development and engineering design big data, the technological paradigm shift presents new

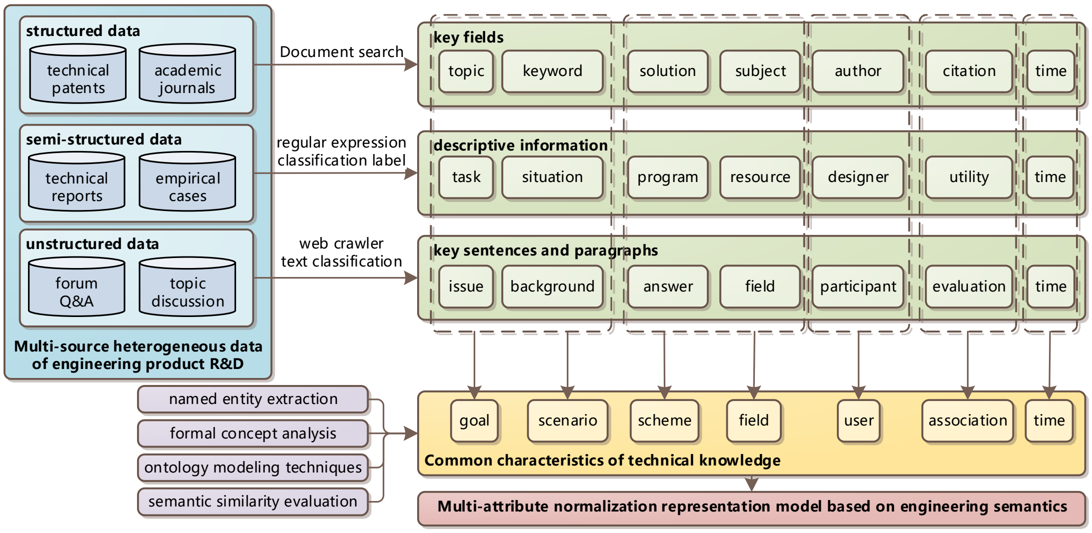

Figure 1. Data mining and semantic analysis for massive big-data in product development and engineering design

features and new forms that are different from previous single areas, single audiences, single dynamics and single models. This paper exploits and analyzes in depth massive multi-source heterogeneous engineering big data with multi-view, multi-temporal, multi-dimensional and multi-granularity, as shown in Figure 1. Our method integrates a variety of advanced text mining methods, such as natural language processing, ontology modeling, semantic network, semantic similarity evaluation, etc. Different sources and different structures engineering text, such as technical patents, journal articles, empirical case documents, professional Q&A forums are fully considered. Data mining and semantic analysis algorithms for engineering big data are developed and improved. Technical knowledge in massive multi-source heterogeneous data is automatically extracted. The engineering semantics is expressed in the form of multi-attribute. It is convenient for computer system to process knowledge automatically.

B. Technology forecasting based on the framework of "Technical Knowledge Evolution-Technological Paradigm Shift-Technological System Revolution"

Patterns, potentials and rates of technology hotspots are evaluated with focus on the future trend of technological paradigm development, based on the framework of "Technical Knowledge Evolution-Technological Paradigm Shift-Technological System Revolution". Multiple technical routes and their possibilities within the limits of technological evolution are forecasted. Considering the micro-breakthroughs, macro-continuation and multi-domain cross-impact features of engineering product technological paradigm shifts, the key characteristics at different stages are extracted, and branch sets of technological evolution are created. This paper objectively and quantitatively describes future possible scenarios of technology developments from aspects of formation conditions, classification and potential estimation of the branches. Based on historical data of technology developments, technologies in different lifecycles and prospects are tracked from the perspective of technology supply side and social demand side. The technology forecasting model and the estimating method for forecasting results are constructed based on a multi-stage technology evolution mechanism. This provides theoretical guidance and method support for technological management decision-making in the field of big data-driven engineering.

C. Forecasting model of technological paradigm shift for technology supply side and social demand side

With the rapid development of technology in current hotspots, technological paradigm shifts present characteristics of micro-breakthrough, macro-continuation, and multi-domain intersection. Enterprises and governments need to grasp the technological development context. Previous subjective, one-sided, qualitative analysis is no longer satisfied technology forecasting. As shown in Figure 2, in this paper, we use a deep learning algorithm called Long-Short Term Memory (LSTM), which can effectively take advantage of historical data. A technology forecasting model considering both the technology supply side and the social demand side is constructed, by means of regression analysis and multi-domain text meta-analysis. The training set is composed of the data in the entire time series of the technological paradigm transition and the testing set is composed of branch the data sets of the technological evolution. Our approach improves the ability of LSTM cells to process information by the improved "gate structure" and enhance the long-term memory ability of the forecasting model. Through the modified items of the assessment model of technological maturity, the forecasting algorithm adopts different optimization strategies at different stages of technological evolution. By decomposing the branch set of technological evolution, the evolution of each technological subsystem is researched and the process of model training is accelerated. Both the technology supply side (basic theoretical accumulation, bottleneck breakthrough, mature technical diffusion, etc.) and the social demand side (potential user demand, regional market layout, industrial macro-policy, etc.) are considered. Technological forecasting

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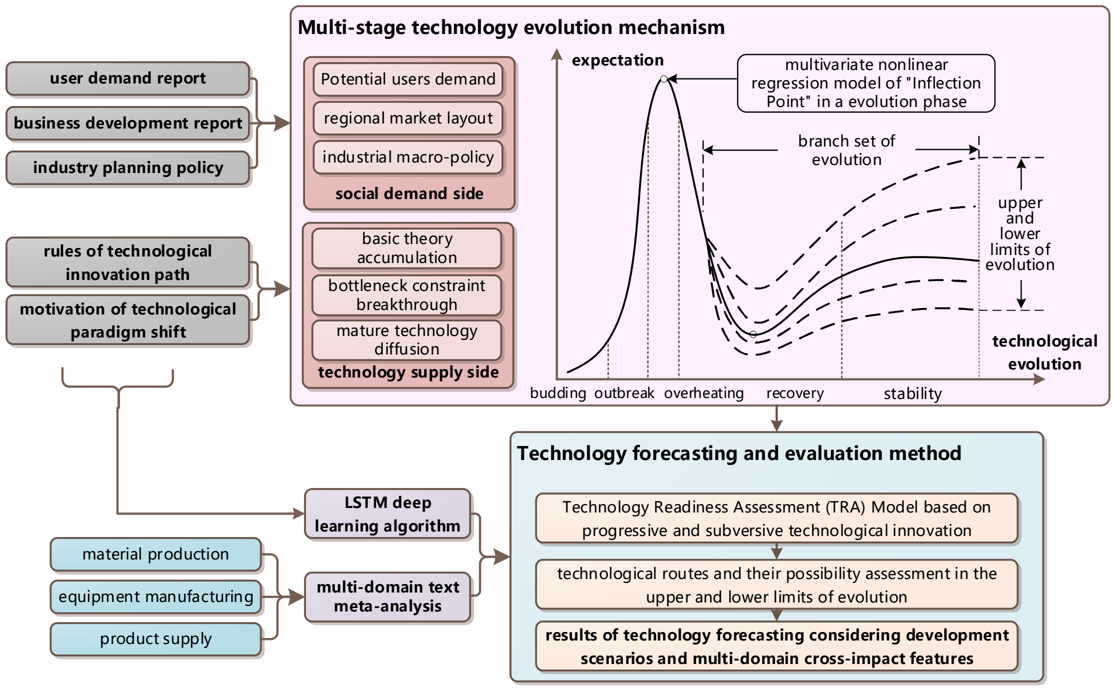

Figure 2. Multi-stage technology evolution and technology forecasting

methods and evaluation methods for hotspots and frontier fields are proposed. Various technological routes and their possibilities for the upper and lower limits of technological evolution are forecasted and analyzed. The trend of engineering technological paradigm shift is forecasted scientifically and reasonably from both perspectives of single-focus technology development and multi-domain cross-impact features.

IV. CONCLUSION AND FUTURE WORKS

Previous technology forecasting methods based on technology hype cycle just consider the external market demand. However, we propose a novel technology forecasting model, which considers both the external market demand and the internal technology evolution law. In this paper, we propose an algorithm framework of technology forecasting based on "Technical Knowledge Evolution-Technological Paradigm Transition-Technological System Revolution". It unifies natural language processing and deep learning in the algorithm framework. The proposal improves the accuracy and validity of forecasting results and provides new ideas for the research in this field. Our research group is carrying out a case study of the algorithm framework of technology forecasting. Some results have been obtained and the experimental results will be published later. In addition, we will compare the proposed model with other models, emphasizing the importance of the proposed technology forecasting methods and expanding this paper.

In big-data driven engineering product innovation, the development routes of technical knowledge and technological paradigm are affected by individual user preferences, R&D team habits, technical field consensus and industrial value concepts. This influence is sometimes abnormal or anomalous. The complexity and variability of knowledge evolution have brought great difficulties to technology forecasting. In this regard, big-data driven technology innovation management and prediction of engineering products must complete three tasks, namely: aggregating and mining the technological knowledge from multi-dimensional and multi-granularity perspectives, modeling and analyzing for technological innovations from multi-temporal and multi-modal perspectives, and observing and forecasting technological paradigms shift from multi-domains and multi-perspectives.

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