Technology forecasting by analogy-based on social network analysis: The case of autonomous vehicles

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ABSTRACT

During the last years, new technologies have been developing at a rapid pace; however, new technologies carry risks and uncertainties. Technology forecasting by analogy has been used in the case of emerging technologies; nevertheless, the use of analogies is subject to several problems such as lack of inherent necessity, historical uniqueness, historically conditioned awareness, and casual analogies. Additionally, the natural process of selecting the analogy technology is based on subjective criteria for technological similarities or inductive inference. Since many analogies are taken qualitatively and rely on subjective assessments, this paper presents a quantitative comparison process based on the Social Network Analysis (SNA) and patent analysis for selecting analogous technologies. In this context, the paper presents an analysis of complex patent network structures using centrality and density metrics in order to reduce the lack of information or the presence of uncertainties. The case of Autonomous Vehicles (AVs) is explored in this paper, comparing three candidate technologies which have been chosen based on the similarities with the target technologies. The best candidate technology is selected based on the analysis of two main centrality metrics (average degree and density).

1. Introduction

During the last century, science and technology have developed at a rapid pace, especially in the past few years. However, although the development of new technology is related to previous successful technology in the market, it is at the same time accompanied by failure. In order to reduce and avoid the uncertainties in the market, technology planning and forecasting have become more and more important, particularly, to support decisions of emerging technologies with less market information and to help organizations and governments to align their decisions with high-level objectives. These aspects have been mentioned by many studies, including the importance of patent analysis in technology forecasting (Sasikumar and Mohan, 2014). Moreover, the application of technology forecasting for market strategy and industries has been emphasized at all levels in the competitive global environment, including automotive, pharmaceutical, electronics, and so on (Pelc et al., 1980), because technology forecasting can be used in organizational and strategic procedures to implement technologies and align firms with their business plans (Yoon et al., 2017).

The future of technology development is critical in technology planning. It is required to allocate resources more efficiently. However, due to the characteristics of new technology, a large amount of historical data can be used to reveal and describe the technology development pattern, to characterize it more precisely, and to maximize gains or minimize loss from future conditions (Martino and Joseph, 1993). The development, scale, and timing of forecasting technology are not optimistic, especially in terms of reducing the uncertainty involved in technical systems under different conditions, which is more important and effective for technology forecasting. In this context, technical forecasting provides a signal to adopt or prevent technological change by helping to apply and adapt the technology (Roper and Wiley InterScience (Online service), 2011). Consequently, the prediction process of similar technologies in a historical context based on existing knowledge and information can help to reduce uncertainties and eliminate subjective judgment in the future (Martino and Joseph, 1993; Mcmanus and Senter, 2009). Often, in the absence of market information and consumer surveys, cutting-edge emerging technologies can be used to infer trends in the development of new technologies by analogy.

Technology forecasting by analogy involves a systematic comparison of the technology to be forecasted with the information of earlier
technology that is believed to be similar in all or most important respects (Martino and Joseph, 1993). However, the use of analogies is subject to several problems, such as lack of inherent necessity, historical uniqueness, historically conditioned awareness, and casual analogies. One of the critical points about forecasting by analogy is the natural process of analogy based on the intuition for the technological similarities or inductive inference (O’Connor, 1971). It is necessary to make a systematic check of all the observable characteristics and to minimize the uncertainty before taking priory conclusions assuming the risk that the two are alike on yet unobservable characteristics. The inappropriate selection and inadequate analysis of analogies led decision makers to make poor forecasts of the decisions, and also noted that structured judgmental processes are more effective than others (Armstrong, 1985; Kahнемan and Lovallo, 1993; Neustadt, 1986). Therefore, the key success factor of forecasting by analogy is to choose the right technologies with operational procedures for comparison that are truly analogous to the one being forecast (Cho and Daim, 2013).

In the particular case related to automobile industry, although development models have been used in several automobile-related technologies, there are very few studies for forecasting the development of Autonomous Vehicles (AVs) in the U.S. In this case, AVs was taken as a technology to be used in the case of an analogous method, and to be compared with the actual status of the development of the technology. So far, the estimation of AVs development and forecast models were based on the personal judgment of analogies and no technical strategy developed.

Although preceding studies have mentioned the promising tools, and enhanced the forecasting by analogy, their limitation was that the studies were based on the personal judgment of analogies and no technical strategy was developed. To fill the gap, and to increase the forecasting accuracy, this paper will focus on the companies in the co-patenting network based on Social Network Analysis (SNA) and patent analysis, which are considered as the crucial nodes to connect patented technology and company's strategy. On the other hand, this study takes a fresh analysis in the technological development trend on the time series models and network analysis for the purpose of utilizing quantitative comparison in analogical forecasting. This allows us to compare the dynamic interrelations over time.

In this context, the objective of this paper is to develop a quantitative comparison process based on the Social Network Analysis (SNA) and patent analysis for selecting analogous technologies. Therefore, the paper answers the question of how to choose the right technology by analyzing all the observable characteristics and to minimize the uncertainty before concluding that the technologies are alike. The process will lead to the selection of a better estimation for technology forecasting models. This will help to improve practices in comparison-based prediction, a model used in technology since forecasting autonomous technologies are used as a validation of the results.

2. Literature review

2.1. Forecasting by analogy

Extrapolation for technology forecasting is based on the assumes that the data in the past of a time series contains all the information necessary for the future of that same series (Armstrong et al., 1984). Since there is available data for technologies that have completed their technology cycle, the patterns of these technologies can be applied in other emerging technologies without enough data. According to experimental records or information, the typical kind of similarity in trends, cycles, or even patterns may be obtained and used in other application areas. For instance, the development of radio and TV was used to forecast the future of the internet, and the sequences of changes in the development of computer software were applied to the evolution and maturation of Internet of Things (IOT) (Daim and Suntharasaj, 2009). Technology forecasting by analogy means identifying a pattern of change that happened in similar technology and applying that same pattern and historical data to predict the possible futures of a new technology. While some earlier technology is believed to have been similar to the new technology, systematic comparisons between the technologies are needed. The natural process of analogy is based on the intuition for the technological similarities or inductive inference (Martino and Joseph, 1993), which is based on a qualitative method. Most analysts believe that analogy helps to understand the intricacies of what happened in the cases and that they will reduce the uncertainties of the future (Schnaars, 1988).

Analogous technologies need to be selected by following a systematic methodology to reduce uncertainties. An analogy is typically defined as a recognizable similarity or resemblance of form or function, but no logical connection or equivalence – as distinguished from a model (Daim et al., 2013). The structured analog is recognized as the primary approach, describing a judgmental procedure for asking experts to list, rate, and match similar analogies with the target (Green and Armstrong, 2007). A possible analogy should be compared in technological, economic, managerial, political, social, cultural, intellectual, religious-ethical and ecological situations that the affected technology changes (Martino and Joseph, 1993) so that potential analogous technologies should be sought and selected from a wide range of candidates. The analogy system is also built on similar cases, theory, patent, and term of inter-technological comparison (Jun et al., 2017). Moreover, historical analogy and life cycle analogy are often referred to as the link between different candidate technologies. Based on historical data, the phenomenon that co-evolution with other technologies in the patterns, processes, and timescales occurs in the diffusion of emerging technologies (Grübler et al., 1999). For example, by analyzing life cycles of products was demonstrated as the close relationship between software and video cassette recorders and VCR tapes; micro-computers and floppy diskettes; and cameras and photographic film (Bayus, 1987). However, there was no consistency in choosing the right technology in prediction throughout most analogy methods (Jun et al., 2017; Massiani and Gohs, 2015).

Promising new tools in technology forecasting are combined with various fields such as political science, computer science, scientometrics, innovation management, and complexity science (Coates et al., 2001). In this case, many different methods have been used and improved in analogical forecasting, such as Delphi and group interview (Green and Armstrong, 2007), search traffic (Jun et al., 2017), bibliometrics (Daim et al., 2006), technology or product life cycle (Bayus, 1987; Lee Kichun, 2012; Park et al., 2015), averaged analogy method based on parameters of multiple products (S, 2012), technology roadmapping (D, 2013), and R&D investment (Taegu Kim and Lee, 2014). Since various analogy took place in data, life cycle, and other parameters, there is the need for developing of integrated and systematic tools for the technology forecasting method to improve accuracy (Daim et al., 2006, 2013; Yu-Heng Chen and Chen, 2011), and further improvements are still necessary for network analysis and the forecasting method (You et al., 2017).

2.2. Patent analysis

Patent documents have long been recognized as a crucial data source for the study of innovation, strategy decision, and market value in a sequential time period. Patents contain significant technical information for technological and economic development. Due to the technical and market value of patent information, it is closer to the real network of technological innovation and development compared with papers, news, twitter, and other information. Patent analysis has been regarded as a key method or analytical tool to predict future scenarios of technology evolution.

Most patent analysis has been integrated into various researches that focused on the possibilities or potentials of technology advance. For example, patent analysis has been utilized for technology
opportunity analysis to forecast emerging technologies by employing text mining and bibliometric analysis (Liu and Wang, 2010). The temporal bursts of R&D activity in patents have now been used to detect the novelty of a new technology field (Hu Yanqing et al., 2010). Meanwhile, patents in emerging technologies have been considered as having a significantly higher impact on subsequent technological development (Aliaibary et al., 2015). Patent indicators are widely analyzed to assess whether the technology is promising (Zager, 2003). Most researches focused on the evolution of certain technology, which is based on the systematic analysis of patenting activity. However, it is seldom discussed the evolutionary paths of different technologies over the same stage of time. The comparisons in patent analysis can be applied into structuralizing, statistical analysis and visualization of patent information (Jeong and Kim, 2014), to support patent-based technology forecasting more efficiently.

Based on the factors of technological changes, it is important to compare the scenarios in the technology evolution, evaluate the risks, and explore the opportunities of technology development. To compare different technologies, patent network analysis tries to illuminate the way to identify more functions, structures, or trends over time, such as the number of patent applications, R&D collaborator, and technological relevance based on citation, et al. There are many technical bases or features that can be compared based on patent analysis, including cooperative network (similar scale of R&D cooperation), co-occurrence network (same technical topics or classification) and citation network (similar technical basis). Thus, we believe that patent documents apparently convey various kinds of observable information for anticipating and understanding the technological change in analogous forecasting.

Patent application activities and cooperative behaviors largely promote the development and commercialization of technologies. Seemingly different technologies are comparable if they are in the same stage of technological development. The first link is between the number of patent applications and patentees within a certain time period, which enables the quantitative study to identify the technology life cycle. Patent life cycle has been used as an S-curve to predict the development trend of a specific technology in terms of the cumulative patent amount (Goffi, 2005). The linear regression based on patent data was used in three S-curve models for measuring the inflection point, the growth, and the saturation time of the technology, which foresees the development trend (Liu and Wang, 2010). The second is cocollaboration, which is used as a knowledge spillover or competitive strategy for companies developing technology together. When technologies grow, the networks of patent collaboration become denser. In the current open innovation ‘paradigm’, most firms open and collaborate with external partners for accessing complementary resources, reducing cost and risk sharing, and faster product development (Jeong and Kim, 2014). Based on the time series models and network analysis, the technological development trend was used to forecast greater development potential (You et al., 2017).

2.3. Social network analysis

Social network analysis (SNA) is considered as a quantitative method to identify how actors interact with each other within a network. Many complex systems can be represented as networks, which could simplify functional analysis considerably (Hu Yanqing et al., 2010). Many network analysis applications are based on topological comparison of complex networks, such as classification and clustering. Given two networks of different technologies, the structural similarity of two networks is possible to compare in measurement such as density, clustering coefficient, degree distribution and so on. Moreover, the graph isomorphism is considered as identical topology to reveal the correspondence between nodes of networks, which is hard to identify the overall structural similarities (Aliaibary et al., 2015; Zager, 2003).

In many studies, technology network analysis has been used to reveal the relative importance of technology areas (Ding Ma et al., 2016), evaluate and compare the significance of communities in different networks (Chen and Fang, 2009; Hu Yanqing et al., 2010), and to visualize the overall structure of a network (Chen et al., 2012). Complex network theory, as well as social network analysis, are used to investigate the social network structure evolution of technology in term of global network properties, major actor’s centrality and collaboration relationships (Ding Ma et al., 2016). To be specific, the cooperative network of patentees can explore the cooperative relationship of R&D innovation. The patent citation network can analyze the path of technology evolution, and the patent co-occurrence network can explore the frontier fields of technology development. The visualization of a timeline plot for each technology network is drawn as a function of size, average age, and time (Chen et al., 2012). Based on patent citation networks, the position of applicants within networks is identified to explain applicant behavior in the marketplace such as cooperation or patent infringement trials (Park et al., 2018). Another technology network is based on the occurrence of core terms and provides a way to understand technological evolution in details and to forecast future opportunities (Huang et al., 2017). The previous studies implied that the comparison between complex network analyses in sequential time periods can capture the more detailed information of interactions in the process of development.

The technology analogy prediction analysis assumes that in a specific innovation environment and with expected benefits, a series of technologies can be improved, rapidly spread, and widely adopted over time, depending on the competition and cooperation of companies in the market. These companies actively participate in patent applications to protect and improve products and technologies in the market and to promote the development of the industry in the process of technology development and maturity. Despite the importance of competition and cooperation, little attention has been paid by analysts to the companies as key players to be compared in the processes of technological accumulation. Based on the theory of social network analysis, we applied the collaboration network analysis to identify the extent to which various candidate technologies act as a similar pattern or trend within the network. The visualization comparison of different technologies showed a direct way to identify technology evolution. The complex network is used for forecasting by analogy, mainly considering that the technology grew quickly and became more complex, thus the current judgment of analogy based on certain characteristic cannot reveal the development track of the underlying innovation system comprehensively and objectively. In this paper, the cooperative network structure is selected for analogy prediction to reveal the leading role of R&D innovators in the underlying innovation system, which is also the basis to promote the continuous development and maturity of industrial technology.

The purpose of this paper is to find analogical technology that is similar to the target emerging technology and have been successfully commercialized. We believed that the cooperation network can be considered as identical topology to reveal the evolution of innovation and market features. A large fraction of major actors represents and control the technology trajectories and market. This means that the need for market protection continues to grow, which will accelerate, in turn, the commercialization process.

2.4. Autonomous vehicles in the US

We chose autonomous vehicles as our case study. Carmakers are always trying to stay ahead of the automobile industry so they can develop cars that markets purchasers will buy in the future. There is a wide agreement in the general car industry that autonomous vehicles are the future, as evidenced by the significant research and development (R&D) investments from automotive players and tech giants alike. Much of the doubts are from common views and perceptions about autonomous cars within the industry, and from misinformation from
During the last years, the use of patents and SNA to forecast and simulate technologies has been applied in a variety of cases and industries such as autonomous vehicles. For example, the analysis of knowledge (by patents) and the importance of building information technologies (Park et al., 2018), analysis of the technology lifecycle for forecasting future trends of semiconductor industry (Chiu and Su, 2014), and forecasting central technologies (key technologies) (Jun, 2012b).

Posteriorly, the combination of using patents and SNA to forecast technologies has also focused on the particular case of electric, autonomous vehicles, and elements of the system of this type of vehicles. For example, patents of Battery electric vehicles (BEVs) are analyzed by SNA to identify core companies to forecast the BEV’s future (Yun et al., 2016). Additionally, the technological knowledge of ecosystems of battery electric vehicles (BEVs), hybrid electric vehicles (HEVs) and fuel cell electric vehicles (FCEVs) can be seen by analyzing

### 2.6. The use of patent data and SNA to forecast and simulate technologies

The analysis of patents by Social Network Analysis has been used in different aspects and the complexity of its use evolved through time. First, patents and SNA is used to analyze the structure of technologies by bipartite network SNA graphs to see the technology clusters and then used them to forecast the technology (Jun, 2012a). Posterior analysis has been done in the side of isomorphism and analysis of trajectories of technologies (Weng and Lai, 2010), quality of patents and its prediction by using patent citation (Wang et al., 2010), and the use of statistics and statistics models of patent networks to forecast technologies (Jun, 2016; Jun and Sung Park, 2013).

Additionally, IT companies related to this type of vehicles are Apple, Amazon, Alibaba, Google, Uber, and Baidu. Considering the dynamics of the relationship between technology, business model, and market, the number of patents related to autonomous vehicles increases based on the development of the knowledge-based economy. At the same time, business model patents for autonomous vehicles grows less than the increasing number of cited patents and the business model respectively (Yun et al., 2019).
Technological Forecasting by analogy based on the social network analysis

Step 1: Bibliometric Analysis of AVs (observable characteristics: Paper, Fund, Patent, News)

Step 2: Survey the similar candidate tech lists for analogy (Literature Review + Experts)

Step 3: Filtering techs based on Technology life cycle (Time normalized based on maximum number of patents)

Step 4: Build technology collaboration networks (whole network & Subnetwork in different time periods)

Step 5: Compare networks in SNA indicators
   - Network Connectivity: Average degree
   - Network Efficiency: Density

Fig. 1. Overall process of the proposed methodology.

the technological knowledge areas (Aaldering et al., 2019).

3. Research methodology

In this section, we introduced the methodology used in this study and explain the steps and sequential strategy to the data. Fig. 1 indicates the five steps for the process of the analogy. First, this study explores the technology development from basic research to social media based on bibliometric analysis, and the development trend of target technologies was analyzed to identify the trend and patterns of change. Second, to facilitate the comparison of technologies generated in different periods, time and trends were normalized based on the maximum number of patents for the S-curve in the technology life cycle, which was helpful to identify the technology life periods within the same process of development. Thus, the periods for each subnetwork were divided into six-time spans with five years each, which enabled us to capture the characteristics of each technology development period. Third, the collaboration networks of patent applicants were built. Companies that filed patents were abstracted as nodes, and co-parenting behavior was depicted as edges. Subnetworks per each period of technology candidates were built, and two main centrality metrics were considered to compare the subnetworks: Average degree and density.

In this study, we proposed a dynamic analogy process in the collaboration network for the same period of growth based on the SNA measures and visualizations. According to previous research, as a field develops, it undergoes a topological transition in its collaboration structure between a small disconnected graph to a much larger network, where a giant connected component of collaboration appears (Bettencourt et al., 2009). These kinds of studies show that the evolution of technology could be observed by the quantitative measure of the collaboration network. Therefore, we built and compared the technology collaboration network (Fig. 2) in order to apply SNA to identify similar technology within various parameters (Table 2).

4. Results and analysis

4.1. Data source

This paper combined SNA and patent analysis methods to compare the trajectory and characteristics of related technologies and tried to identify the most similar ones. The data sources used in this paper were the paper publication from Web of Science (WOS), patent applications from Derwent Innovation Index (DII), engineering papers from Compendex, grants from Nation Science Foundation (NSF), and news from EBSCO related to autonomous vehicles. We collected patent data in the DII based on Derwent Manual Codes (DMC), which is a hierarchical indexing system used for patent retrieval and analysis. Under the advice of the experts, we retrieved data on April 19, 2018, with all the patents filed in related candidate technology fields of US Autonomous Vehicles (AVs) in the automobile industry, including Electricity Vehicle (EVs), Hybrid Electricity Vehicles (HEVs), and Fuel Cell Vehicles (FCVs). The value of various indicators was obtained via Ucinet to measure the collaboration graph.

The data sources, which were selected according to the technology life cycle, are indicated in Table 3. The journal papers were used to describe the fundamental and applied research, while the patent data was used to the technology trajectory based on SNA. The number of grants was an indicator that helped to describe the effects of incentives for R&D in the development of the technology.

4.2. Bibliometrics analysis of autonomous vehicles in the US

Based on bibliometric analysis of the development trend of American autonomous vehicle technology in the U.S., over the past five years, self-driving vehicle technology has gained significant attention with the rapid growth in U.S (Fig. 3). Social media and R&D investment, while the growth rate of applied engineering and basic research has been slow and fluctuating. The number of company patent applicants has also been increasing. By 2017, there were around 400 related enterprises and institutions in the U.S. The patent race of autonomous vehicles has become more and more competitive among both automakers and tech companies. The R&D budget rose 20% for tech players and 5% for automakers. According to research conducted by Oliver Wyman and WIPO, between 2012 and 2016, there were slightly > 5000 mobility patents filed by 12 leading automakers and global tech companies (Chen and Fang, 2009) (Fig. 4).

According to the patent application trend, it is obvious that AVs technology in the U.S. can be divided into three phases. Before 2007, the study of AVs in the U.S. was in the period of accumulation and exploration around the “Grand Challenges” that remarkably accelerated advancement (Anderson et al., 2016). From 2008 to 2012, Google's driverless car initiative was in place and moved to complex city streets. In 2013, more companies, such as Audi, Toyota, Intel, etc., began to enter the driverless car industry and unveiled R&D plans, visions, and roadmaps. This is consistent with the U.S. self-driving technology development and the expectation of experts in the U.S. market. We believe
that compared with data sources such as news, papers, and fund projects, patent documents can better reveal the performance of technologies in the market.

### Table 2

SNA indicators for comparison.

<table>
<thead>
<tr>
<th>Network</th>
<th>Dimension</th>
<th>Indicators</th>
<th>Definition</th>
<th>Meaning for high values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Whole network</td>
<td>Size of network connectivity</td>
<td>Average degree (AD &gt; 0)  H-Index (HI &gt; 0)  Degree of centralization (DC)</td>
<td>Number of average links of nodes  Highest number x so that there are x vertices of degree at least equal to x  The overall network degree centralization</td>
<td>High amount of connections in the network  Higher concentration of nodes with a high degree  High quality of nodes (central) on the network with significant direct influence on their contacts</td>
</tr>
<tr>
<td>Density of network efficiency</td>
<td></td>
<td>Density (0 &lt; DE &lt; 1)  Connectedness (0 &lt; CN &lt; 1)  Avg distance (APL &gt; 0)  Diameter (Di &gt; 0)  Compactness (0 &lt; CM &lt; 1)  Efficiency (0 &lt; EF &lt; 1)</td>
<td>Number of links divided by the maximum possible number of links  Number of not reachable vertices  Average geodetic distance between reachable pairs  Length of the longest geodetic distance  The adjacent distance of all nodes  Extent to which underlying networks have redundant links</td>
<td>High density in network  Not fragmented  Significant distance between the nodes  Significant distance between the nodes  Greater cohesiveness  Lower density</td>
</tr>
<tr>
<td>Subnetwork</td>
<td>Connectivity</td>
<td>Average degree</td>
<td>Average of the degrees of all the nodes in the subnetwork</td>
<td>High amount of connections in the subnetwork</td>
</tr>
<tr>
<td>Density</td>
<td>Density</td>
<td>The number of links divided by the maximum possible number of links in the subnetwork</td>
<td>High density in the subnetwork</td>
<td></td>
</tr>
</tbody>
</table>

### Table 3

Data source.

Source: Based on information from Chiu and Su (2014).

<table>
<thead>
<tr>
<th>Source</th>
<th>Type of source</th>
<th>Technology life cycle indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Web of Science (WOS)</td>
<td>Journal papers</td>
<td>Fundamental research</td>
</tr>
<tr>
<td>Compendex</td>
<td>Engineering paper</td>
<td>Applied research</td>
</tr>
<tr>
<td>Grants from National Science Foundation (NSF)</td>
<td>Number of grants</td>
<td>Social impact</td>
</tr>
<tr>
<td>News from EBSCO</td>
<td>Newspapers</td>
<td>Social impact</td>
</tr>
<tr>
<td>Derwent Innovation Index (DII)</td>
<td>Patent application</td>
<td>Development</td>
</tr>
</tbody>
</table>

4.3. Technology life cycle

The growth curve method is about fitting the growth curve into a set of data on technical performance and then extrapolating the growth curve beyond the data range to get an estimate of future performance (Yu-Heng Chen and Chen, 2011). The adjustment of the growth curve works better when there are enough existing data, and the assumptions about limits, parameters, and trends are close to realistic and existing conditions. However, when the information is limited, the trends of the curve can have many alternatives depending on the decisions defined by the assumed trend. For such a situation, as indicated above, is to use the pattern and characteristics of the technologies that have completed their cycle. The use of the pattern of these technologies as analogies requires systematic steps to evaluate the analogous technology, assumptions, and adjustments to be taken. Step 3 in the presented method can be applied to the following conditions and steps:
- The target technology is in the stage of growth (the case of AVs).
- The S-curve is used as the pattern of the cycle. Therefore, it is required to obtain the curve, including calculation of parameters, estimation, and drawing the S-curve for candidate technologies.
- Normalization of the time periods.
- Division of the cycle in periods that cover each stage of the cycle (six time periods for the analysis of AVs).

Due to the fact that the life cycle of all candidate technologies could correspond to different periods and have different characteristics, the curves need to be normalized for the candidate technologies. The critical points to be normalized are based on the time (year) and the alignment of the technology life cycle stages. The time normalization corresponds to the time identification of the absolute maximum point of the curves and the corresponding lags of time that each technology needs to have to coincide with the maximum points.

At the same time, the elongation of each part of the curves needs to be considered. This is an important point since the development of each technology could take a shorter or longer period of time. However, one of the important points to consider is that the candidate technologies are chosen based on their similarities to the “objective technology” (AVs). Since the candidate technologies have similar characteristics, adjusting the life cycle curves to one common point will show that the technology life cycle curves may have similar trends and shapes.

Another important point is that the analysis needs to be divided into periods that cover each stage of the technology life cycle curves. In our case, the time period was 44 years, which was divided into six four-year time periods. This is was for two reasons, one was that the number of theoretical stages, the networks, and their respective connections, were built in “periods”. Therefore, this process allowed for the synchronization of the theoretical stages, the network characteristics by period, and the “elongation” of each stage. The curves’ elongation characterizing the time that each technology takes to reach the maturity level is an important element to be analyzed. This characteristic principally implies the different time duration in each stage of the curves. Fig. 5 characterizes the technology life cycle and the stages that need to be identified and characterized.

The three technology life cycle curves had close characteristics. The main differences were shown in the amplitude or number of patent applications. Fig. 6 shows the three candidate technologies. EVs and HEVs technologies’ life cycles were very similar in terms of the number of patent applications and their time differences in each stage; however, the time differences needed to be considered. The differences between FCs is more evident, especially in terms of the number of patents. In order to see these differences more clearly, Fig. 7 shows the differences in time of each stage in each technology (the circumferences in green denote the year-subnetworks).

Table 4 shows the time period of each technology and for each stage, which comprises of six four-year periods. It can be observed that the “emerging stage” is the longest period, following by the growth stage, and then the maturity stage.

4.4. Technology collaboration networks

The patent co-ownership network can be used to construct un-directed technology networks by identifying the whole and sub-network of collaboration relationships. When the technology grows, the number of companies who file patent applications will increase accordingly and their networks of cooperation also become denser. This means that the
need for market protection continues to grow, which will in turn accelerate the commercialization process. Based on the analysis of the candidate technical cooperation network, the indicators of the candidate technical cooperation network were calculated to compare the overall situation of the candidate technical cooperation. Table 5 shows that AVs and candidate technologies are similar in the network connectivity and density with tiny differences. HEVs are probably the most notable in the performance of connections and efficiency with the highest connectedness, distance, diameter, and compactness in the whole network. This can also indicate that hybrid cars may be far away from AVs when compared to others. We found some evidence in the U.S. market that HEVs are now perceived as a core segment of the automotive market. American sales of hybrid electric vehicles represent about 36% of the > 11 million hybrids sold worldwide (Cobb, 2016), which is different from the AVs in the early development process.

However, the whole network cannot reveal and compare the characteristics and network structure of technological development and evolution. If the social network indicators of the overall technical cooperation network are similar, this can indicate that in these technical fields there are similar cumulative numbers of companies who participate in technology creation and improvement and that actively pursue the market protection.

In practice, the collaboration networks based on paper co-authorship expressed that the average number of edges per node tends to increase over time (Bettencourt et al., 2009). When technologies grow, their networks of collaboration either in the publication or in patent documents also become denser. So we referred to the densification laws of the scaling exponent proposed by Leskovec et al. (2005) to compare the growth patterns in candidate technologies.

edges = A(nodes)^α

where A and α are constants. The scaling exponent, α, expresses the densification effect in a way that is independent of scale (number of nodes) (Table 6).

Fig. 8 shows that the EVs and AVs show a significant increase in the number of edges per node as the field grows (α > 1). In the light of densification and growth by time, there are two possible conclusions. First, when exponent α was around 1, it showed a constant average degree over time, so for EVs and AVs, it was not extremely dense and they were still in the early stages. Second, although the application year for EVs was later than AVs, the collaboration network of EVs increased in density, which means probably more innovators participated in this area and EVs were adopted faster than AVs. In addition, when comparing technologies based on the trend of the overall technical cooperation network, it was difficult to make a comparison in view of the different development cycles of technologies. Therefore, it was necessary to analyze different time intervals of the candidate technology, and then calculate the cooperative network indicators to compare the development process of different technologies.

Fig. 9 reveals a collaboration subnetwork structure at different times. In terms of self-driving technology, which was invented earlier than other candidate technologies, there have been great technological advances, and the cooperation network has become increasingly dense in the past decade. Companies are still in a period of full bloom. However, technology cooperation networks in EVs, HEVs, FCVs are becoming more centralized, especially EVs and HEVs. Their cooperative relationship between companies is closer than ever.

The density and average degree of the subnetworks during the first stage is clearly less dense as compared with the stages closer to the maturity stage. The average density is the average of the degrees of all nodes in the network (sub-networks) and measures the connectivity level of the network. Additionally, the density of the network (sub-network) measures the efficiency of the network by dividing the number of links by the maximum number of links. These metrics were measured in each subnetwork and for each technology.

The average degree and the density metrics were calculated in each

![Cumulative of Number of Patents (standardized Time)](image)

**Fig. 7.** Candidate technologies life cycle stages: EVS, HEVS, FCVS.
period for each technology (see Fig. 10). As it was expected, the curves for the density followed similar patterns. In terms of density, these close values confirmed that these technologies follow similar patterns. However, a clear difference was shown in the earlier stage, especially for the values of density. This can describe the differences among each technology due to differences in starting time (starting at the emerging period), and the knowledge of certain technology. In terms of average degree, the number of connections among patents increased according to the periods closer to the maturity stage.

In order to compare the curves, and choose the most representative one, the variance was calculated with respect to the average points in each period. The formula to calculate the variance, where \( x \) represents the values of the centrality metrics, is presented below. The curve with the lowest variance was chosen, in this case, the FCVS, where both connections and density variance were the lowest.

4.5. Compare real values with found analogous technology

As it is seen in the last two figures, the selected technology had a better approximation to the target technology trajectory (Fig. 11). The cumulative number of patents of FVCs was similar to the AVs trajectory in two aspects: one was the number of patents in each year, and the second was that the elongation of the curve gave a better approximation to trends over the long run.

4.6. Technology forecasting based on selected analogous technology

Based on the selected technology to be used as analogous (FCVs), it is possible to forecast the performance and know the trajectory of the technology. Since this paper utilizes the number of patents as the database, it is used the parameters and characteristics of the growth curve of the selected technology (FCVs) to estimate or fit the growth curve of the target technology (AVs).

The applications of the technology forecasting are extensively explained by the existing literature which is mainly based on growth curves such as the Bass Model, Lotka-Volterra Method, Pearl Curve, and Gompertz Curve (Chiu and Su, 2014). Based on the characteristics of the technology, the symmetry of the curve, the potential substitution of AVs in the market, existing past progress or unexploited early improvements offset the fact that stimulate growth, the Pear growth curve.
is used following the curve (Martino and Joseph, 1993):

\[ y = \frac{L}{1 + ae^{-bt}} \]

- **L** = Upper limit to the growth of variable y
- **e** = Base of the natural logarithms
- **t** = Time
- **a, b** = Coefficients of the curve

In order to estimate the parameters of the curve, the formula can be expressed as (Martino and Joseph, 1993):

\[ y = \frac{L}{1 + a10^{A-Bt}} \]

\[ Y = \text{LOG}\left(\frac{y}{L-y}\right) = -A + Bt \]

As **a** and **b**, **A** indicate the location and **B** the shape of the curve, but with different magnitudes (Martino and Joseph, 1993).

First, the parameters **A** and **B** are estimated based on the cumulative number of patents for the FCVs (Fig. 12). These **A** and **B** values are taking for shaping the forecasting curve of AVs and the limit value of **L** is adjusted to the new conditions of the patent and maturity level of the technology. The estimated parameters and the limit value are:

| **L (AVs)** | 40,000 |
| **A** | 314.9616 |
| **B** | 0.156563 |

### 5. Discussion

This section will address the “so what” question for the research presented in this paper. The paper makes both methodological and application focused contributions. We will explain these contributions below:

#### 5.1. Methodological contributions

The paper makes multiple methodological contributions as listed below:

- **Research presented in this paper introduced an integrated methodology for analogy based technology forecasting as shown in Fig. 1.** The integration of multiple methods as described throughout the paper provides a repeatable process for researchers as well as practitioner professionals. Prior research on technology forecasting using analogy has not provided such a platform approach before (Jun et al., 2017; Kwasnicka et al., 1983; O’Connor, 1971). The paper builds upon the earlier work (Gonçalves Pereira et al., in press; Lin et al., in press; Cho and Daim, 2016; Daim et al., 2012; Gibson et al., 2017) which provided earlier integrated platforms for technology forecasting.

- **The paper also makes point contributions.** Integrated use of multiple data sources ranging from publications to grants demonstrates another repeatable platform building upon earlier work using some of these data sources (Gonçalves Pereira et al., in press; Lin et al., in press; Cho and Daim, 2016; Daim et al., 2012; Gibson et al., 2017; Madani et al., 2017; Madani et al., 2018).

- **Use of SNA in technology forecasting is not new (Behkami and Daim, 2012; Garces et al., 2017; Marzi et al., 2017).** However, using SNA to identify collaborations and using collaboration density for analogy purposes is another contribution presented in this paper.

The paper also makes contributions through the analyses of the autonomous vehicle case. The following is what we learn through the analyses.

- **Self-driving vehicle technology has gained important attention with the rapid growth in U.S. social media and R&D investment, while the growth rate of applied engineering and basic research has been slow and fluctuating.** The invention race in autonomous vehicles has become more competitive among both automakers and tech companies.
Technology life cycle stages as well as collaboration networks and their dynamics for emerging automotive technologies were identified.

Final analysis based on the prior points reveal that major invention activity in the autonomous vehicle technology is maturing and we should start seeing this industry pick up soon. Of course technology alone is not just the enabler. Technical innovations will always depend on other types of innovations including social, political or ethical.

6. Conclusions

There are several key conclusions in this paper. The first set is methodological:

- This paper describes the most important aspects about selecting candidate technologies to be considered as an analogous technology in order to forecast the development of technologies, given the lack of data to fully describe the trajectory of target technologies. In this context, the information of patents is used with using SNA that allows the analysis of the complex structure of patent networks. The analysis of complex networks is important since it allows finding patterns and fill the gap of lack of information and reduce the uncertainties.
- The paper takes AVs technologies as a technology to be analyzed and tests the data and results. Three candidate technologies were considered that were chosen based on the similarities to the target technologies. To fill the lack of a method that provided systematic steps to select the best candidate technology, this paper proposed steps and described an application case. To select the best candidate technology, the paper describes, based on the technology life cycle, the main characteristics of the candidates based on journal papers, grants, and the news media. Based on the selected technologies, SNA was performed based on patent data. The best candidate technology was selected based on the analysis of two main centrality metrics (Average Degree and Density), and finally, we selected the technology based on the lower variance of these metrics.

The second set are in respect to the automotive technologies.

- The paper clearly identified the invention activity and the stages of technology life cycle for the emerging technologies. These can be critical in assessing and new emerging technologies
- The paper also identified collaboration networks and their density
over time. This also can be essential in assessing new emerging technologies in this area.

Finally the forecast shows that future growth of autonomous vehicles will not so much depend on new technological inventions but more likely on complementary innovations in the product, regulation or social systems.

7. Limitations

The paper presents an alternative to fill out the gap of using quantitative methods for forecasting technologies when there is a lack of enough data and taking as a reference the technology trajectory of similar technologies that have completed already their lifecycle. The use of patents and their structural analysis by SNA is presented as the
alternative; however, the paper focused mainly on trying to find quantitative arguments to select technologies (similar technologies considered as “candidates” which has completed their technology life-cycle already). Therefore, future analysis of this approach is needed to find out more explicit models that can help to the reasoning and arguments.

Additionally, the “candidate technologies” (EVs, HEVs, PHEVs) has been determined according to the similar technologies to AVs in this paper; however, these alternatives can be adjusted incorporating or obviating any of them.

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