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Forecasting technology success based on patent data

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ABSTRACT

A novel method for forecasting technology success based on patent data is proposed. Four criteria, technology life cycle, diffusion speed, patent power, and expansion potential are considered for technology forecasting. Patent power and expansion potential are considered as technology scope indicators. A data fusion algorithm is applied to combine the results obtained from different criteria. The usefulness and potential of the proposed forecasting approach has been demonstrated using all U.S. patents related to three technologies, namely thin film transistor-liquid crystal display, flash memory system, and personal digital assistant. The results obtained from these patents demonstrate that the personal digital assistant technology is preferred over other technologies. Investments in thin film transistor liquid-crystal display and flash memory system technologies have equal priority.

1. Introduction

Decisions related to investments in any technology are affected by different factors such as marketing, human resources, location, etc. Prediction of benefits from investment in a new technology is of great interest. Forecasting the success of future technology is key to the decision makers. Because, knowing or predicting the success of invested technology provides important clues, such as the current technology life cycle of the technology under consideration, diffusion potential and technology scope. In technology and business, it provides planners to choose the right strategies for the future (Kassicieh and Rahal, 2007). Therefore, the future technology success should be predicted prior to investment decision.

Patent data may be used to predict the success of technology when analyzed in the context of technology life cycle (TLC), diffusion potential, and technology scope (patent power and expansion potential). The future technology success of the investment alternatives has not been forecasted based on patent data in the context of these four criteria in the literature so far. To fill this gap, the answer to the question of how future technology success for investment alternatives can be forecasted is researched in this paper. Therefore, a novel method based on patent data is proposed to forecast technology success.

There is a need to develop a technology forecasting (TF) method to predict future technology success. In this paper, TLC phases, initiation, growth, and saturation, are used with (i) the diffusion potential of the technology to determine possible acceptance, and with (ii) technology scope to determine the strength of the relationship of the technology with other technologies. It should be noted that patent power and expansion potential are used as indicators of technology scope. The total number of International Patent Classification (IPC) codes included in retrieved patents is divided by the total number of

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patents for the measurement of patent power (see expression (2)). In addition, the total number of different IPC codes found in the retrieved patents is also considered as expansion potential.

Patents are an objective indicator for technology forecasting (Chang et al., 2009). They also provide up-to-date and reliable knowledge for the identification of technological trends (Yoon and Kim, 2012a). In addition, they are useful in forecasting technology (Campbell, 1983) and technology decision-making (Jaranyagorn and Ngavej, 2012). Ernst (1997) showed that patent data was suitable for TF. Although there is a lack of quantitative approaches that are proposed for forecasting the future of technology, some studies have also suggested a quantitatively-based TF method. In the present study, patent analysis is used to quantitatively forecast the future state of technology. In addition to patent analysis, we also use the Condorcet method, which was developed by Condorcet (1785), to combine different results from each considered criterion and to prioritize technologies. The Condorcet method, which is sometimes called the Condorcet voting algorithm, is a data fusion method that ranks different results generated from different data resources. Each technology is considered a candidate and each criterion is considered a voter in this method.

The remainder of this paper is organized as follows. The literature relating to technology forecasting studies, technology life cycle, technology diffusion, technology scope and the technologies being evaluated are discussed in Section 2. Following the literature review, a new technology forecasting method is introduced in Section 3, with application of the method being presented in Section 4. The final section will draw conclusions and propose directions for future research.

2. Literature review

The literature surveyed in this paper is grouped into three parts: studies for technology forecasting; literature review of criteria and the technologies being evaluated.

2.1. Technology forecasting

Patent-based technology forecasting (TF) methods reported in the literature are summarized in Table 1.

Various multi-criteria decision-making approaches were applied for selection of TF methods. For example, Intepe et al. (2013) selected the most appropriate TF method for 3D television technology using a TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method. Cheng et al. (2008) compared TF methods for the development of new materials using the fuzzy AHP (Analytical Hierarchy Process) method. A detailed discussion of TF can be found in (Balachandra (1980a,b), Levary and Han (1995), Lemos and Porto (1998), Coates et al. (2001), Mishra et al. (2002), Firat et al. (2008), and Miller and Swinehart (2010)).

Different types of methods were used to forecast the future of the technologies. Among them are; Monte Carlo simulation for televisions (Linton and Yeomans, 2002), grey theory for Taiwan's opto-electronics industry (Lin and Yang, 2003), multiple regression, linear regression, and the growth curve for airplane technology (Lamb et al., 2010), multiple regression models for wireless communication technologies (Patino et al., 2010), bass diffusion model for residential energy management technology (Daim et al., 2010), bass diffusion model for pulsed electromagnetic field therapy as a technology (Pretorius and Winzker, 2010), and Brownian agent-based technology forecasting for Korea's software (Shin and Park, 2009). Harell and

Table 1
Patent forecasting studies.

Author(s) (year)	Technology	Method(s)
Altuntas and Dereli (2015)	Telecommunication technology	DEMATEL method and patent citation analysis
Altuntas et al. (2015)	Database theory and its application	Weighted association rules
Choi and Jun (2014)	Humanoid robot system	Bayesian patent clustering
Li et al. (2014)	Green energy	Patent analysis and simulation model
Chang et al. (2014)	Dental implant	Patent analysis
Ranaei et al. (2014)	Low emission vehicle	S-curve
Jun and Lee (2012)	Nanotechnology	Neural networks
Jun et al. (2012,b)	Biotechnology	Association rules, time series analysis and k-means clustering
Yoon and Kim (2012a)	Silicon-based thin film solar cells and umbrellas	Property–function analysis, network analysis and TRIZ trend analysis
Chiu and Ying (2012)	Building-integrated photovoltaic (BIPV)	Logistic growth model
Lee et al. (2012)	Display	Pareto/NBD (negative binomial distribution) model and gamma–gamma model
Chen et al. (2011)	Hydrogen energy and fuel cell	Logistic growth model
Trappey et al. (2011)	Radio frequency identification (RFID)	S-curve
Jun (2011a)	Database theory and application	Association rules
Jun (2011b)	Image and video technology	Association rules and self-organizing map
Chen et al. (2010)	Hydrogen energy and fuel cell	Bibliometric analysis and growth curve
Jun and Uhm (2010)	Bio-technology	Frequency time series model
Cheng and Chen (2008)	Nanosized ceramic powders	Logistic growth model
Karakan and Koc (2008)	Isolation technology in white goods sector	Pearl curve and technology substitution model
Daim et al. (2008)	Data storage	Bibliometric trend analysis, grow curve and technology cycle time
Yoon and Park (2007)	Thin film transistor-liquid crystal display (TFT-LCD)	Morphology analysis and conjoint analysis
Daim et al. (2006)	Fuel cell, food safety and optical storage	Bibliometric analysis, grow curves and system dynamics
Ernst (1997)	Computerized numerical control (CNC)	Patent analysis

Daim (2009) used the publication data from Science Direct and patent data from World Intellectual Property Organization (WIPO) database to forecast energy storage technologies for future electricity generation. Zhu and Porter (2002) focused on automated extraction and visualization of information for technological intelligence and forecasting. They presented different types of methods for knowledge extraction and visualization of information for TF. Tseng et al. (2002) proposed a hybrid forecasting method based on a neural network model with seasonal time series ARIMA model to forecast Taiwan machinery industry and the soft drink time series. Lee and Shih (2011) proposed novel gray-based cost efficiency for renewable energy technologies. Lee et al. (2014,) developed a technology forecasting method based on analytic hierarchy process (AHP) analysis and factor analysis for prioritizing investments in IT emerging technologies.

The growth curve, also called an S-curve, can be considered one of the most popular methods for TF. The growth curve was conducted for data storage technologies (Daim et al., 2008), renewable energy production (Daim et al., 2012), and 20 emerging technologies under the "Machine and Materials" category (Bengisu and Nekhili, 2006).

The Delphi method was extensively performed for TF in the literature. The method is based on the input data obtained from a team of experts in the relevant field. The method was conducted for open source software (Gallegoa et al., 2008) and nuclear energy (Hussler et al., 2011).

Technology Forecasting using Data Envelopment Analysis (TFDEA) was used in the literature as well. It allows users to consider multiple inputs and outputs for TF. The TFDEA, which was published as a Ph.D thesis by Inman (2004), has been used effectively to forecast various technologies in recent years, such as computer display projector technology (Iamratanakul et al., 2005), fighter jet technology (Inman et al., 2006), wireless communications technology (Anderson et al., 2008; Lim et al., 2012), solar technology (Spatar et al., 2012), liquid crystal display (LCD) technology (Lim et al., 2013), hybrid electric vehicle technology (Jahromi et al., 2013), and mobile phone technology (Dereli et al., 2013).

Details on technology forecasting methods can be found in Cho and Daim (2013) and Walk (2012). In addition, Martino (2003) reviewed recent advances in technological forecasting, such as Delphi, growth curves and probabilistic forecasts.

2.2. Criteria

Among the existing technology forecasting indicators, patents and patent citations are considered meaningful (Chang et al., 2009). Availability of input data for TF is quite important to easily conduct methods for forecasting. Patents can be easily obtained from a patent database because most of the patent databases are freely available and open to the public and all researchers worldwide. There are different types of indicators related to patent data such as citations, patent age, IPC codes, and claims. Gao et al. (2013) emphasized that the current stage of TLC for one technology should be considered to make investment decisions. The S-curve has been widely used by researchers for TLC analysis. The results of Chen et al. (2011) study demonstrated that the S- curve is an effective quantitative technology forecasting method for TLC analysis based on patent data. Technology development track can be effectively understood through TLC displayed by the S-curve (Chiu and Ying, 2012). Altuntas and Dereli (2012) emphasized that the speed of innovation diffusion of technology has to be addressed for investment projects. If the diffusion speed of invested technology is high, this implies that the technology may have higher market potential and innovative activities conducted related to the technology may affect other technologies in the future. Furthermore, the technology scope is related to its economic impact. Investment in a technology that has high technology scope leads to higher economic value and commercialization potential from the investment. If a technology is at the growth stage of its TLC, has high diffusion potential and wide technology scope, this technology can be considered a successful investment. Therefore, four important TF indicators for investment projects are used: (i) technology life cycle (TLC), (ii) diffusion speed of invested technology and technology scope including, (iii) patent power, and (iv) expansion potential in this study. These indicators are explained in the following subsection.

2.2.1. Technology life cycle

Technological investments should be analyzed with respect to their current life cycle stage (Haupt et al., 2007). Liu and Wang (2010) introduced three stages of the technology life cycle, namely: initiation, growth and saturation. These stages are illustrated in Fig. 1.

The curve in Fig. 1, also called an S-curve, shows that an investment should be made during the growth stage. Many researchers do not recommend investment at the initiation and saturation stage. During the initiation state, the technology is still new to the market. Likewise, there is a high probability that the technology may be replaced with a newer technology in the saturation stage. Actually, investments can also be made at the end of the initiation stage and at the beginning of the saturation stage if the investor can take risks. The approach proposed in this paper assumes that the investments are beneficial if they are made during the growth stage. In this paper, the cumulative number of patents is used to determine the current life cycle stage of technologies to be invested in. TLCs for the technologies assessed use curves involving the cumulative number of patents. Details on the assessment of the stage of TLC based on S-curve can be found in (Ernst (1997), Cheng and Chen (2008), Dubarić et al. (2011), Gao et al. (2013)). Extensive studies on TLC have been performed in the last four years, e.g., Gao et al. (2013), Taylor and Taylor (2012), Dubarić et al. (2011), Ryu and Byeon (2011), Cao and Zhao (2011), and Lee (2010).

2.2.2. Technology diffusion speed

Huang and Wang (2011) emphasized that technology can spread and therefore can be used by different firms, organizations and countries through diffusion. Perkins and Neumayer (2005), Xu and Chiang (2005) and Haruna et al. (2010) researched international technology diffusion as a way of examining this process. Patent citation analysis can be used as a way to predict the diffusion speed of various technologies. If a patent is cited by subsequent patents, this implies that the cited patent is diffused, applied and valuable (Chang et al., 2009). Investment in a technology that has high diffusion potential may result in a higher market potential. In this study, the

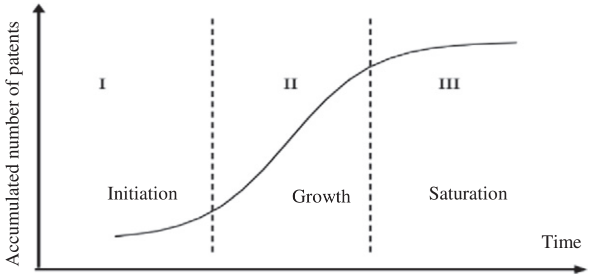

Fig. 1. S-curve of TLC (Liu and Wang (2010)).

average number of citations per patent is used as a proxy for technology diffusion speed (see expression (1)). Details for measuring patent technology diffusion are presented by Huang and Wang (2013).

Technology diffusion speed $= a\,/b$,
where a is the total number of forward citations and
b is the total number of patents that are considered for diffusion (1)

2.2.3. Technology scope (patent power and the expansion potential)

Technology scope criteria assess mainly the breadth of technology. If the breadth of technology is high, this means that the technology has associations with a large amount of different technologies. In this paper, the technology scope is measured by two indicators, the patent power and the expansion potential. Lerner (1994), Jun (2011a), Jun et al. (2012b) and Gao et al. (2013) simplified their data gathering process by using the first four-digits of the IPC (International Patent Classification) code in patent analysis. In this paper, the same four-digit code is used as a proxy for examining the technology scope. The total numbers of different IPC codes in the patent database that are related to our technologies of interest indicate the expansion potential of these technologies. A higher expansion potential implies a higher possibility of the usage of the technology in new technologies covered by these IPC codes. The development of one technology leads to the development of technologies associated with it. Expansion potential indicates the number of technologies that are related to invested technology. Patent power is defined in expression (2). A higher patent power leads to a higher spillover of technology among different sectors and a higher chance of creating new sectors. This implies that the technology of interest has a stronger association with different technologies and potential for the formation of new sectors. Both patent power and expansion potential are computed to measure technology scope and evaluate technologies.

Patent power $= x\,/\,y$, (2)
where x is the total number of IPC codes included in retrieved patents and y is the total number of patents

2.3. Technologies being evaluated

Three technologies are examined in this section. These are thin film transistor-liquid crystal display, flash memory system and personal digital assistant. These three separate technologies are considered to validate the proposed approach and show how it works. They are selected for application of the proposed method because these three technologies are at the growth stage of their technology life cycle and it is not possible to evaluate these technologies quantitatively with respect to their technology success without a method.

2.3.1. Thin film transistor-liquid crystal display technology

Thin film transistor-liquid crystal display devices (TFT-LCDs) have become increasingly attractive and popular due to their full color display capabilities, low power consumption and

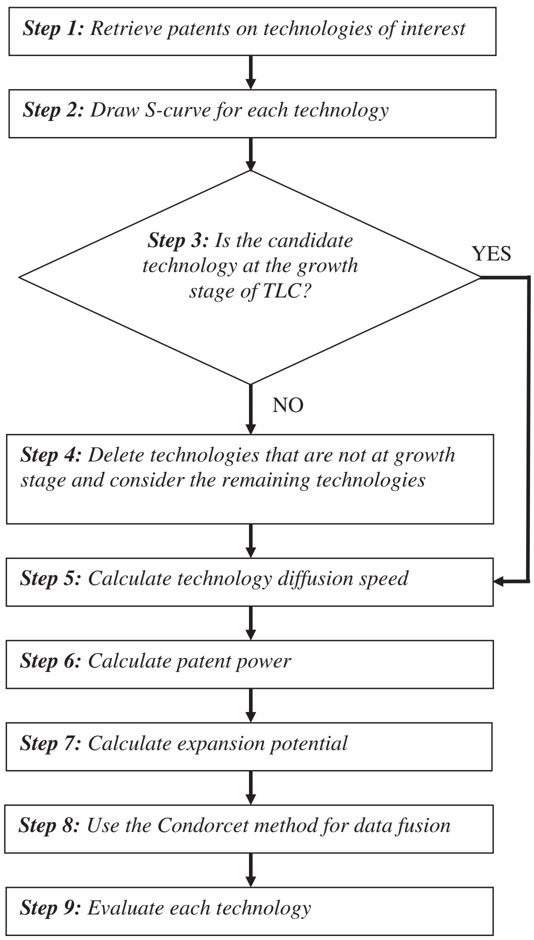

Fig. 2. The proposed method.

Table 2
Summary of data from retrieved patents.

A	B	C	D	E	F	G
TFT-LCD	TFT and LCD	November 13, 2012	178	1316	308	21
Flash memory	Flash memory system	November 13, 2012	363	5693	471	21
Personal digital assistant	Personal digital assistant or PDA	November 13, 2012	313	9546	433	52

A: Technology. B: Query (the research terms are in the titles of the patents). C: Date of retrieval. D: Total # of patents. E: Total # of patent citations. F: Total # of IPC classes. G: # of different IPC classes.

light weight (Lu and Tsai, 2004). They are also thinner, smaller and lighter than other display devices (Lin et al., 2009). Yoon and Park (2005) proposed a keyword-based morphology analysis based on patent data to identify technology opportunities for TFT-LCD technology. The search keyword used for patent analysis was 'TFT-LCD' in their study. They found that the technology is at the growth stage of its technology life cycle based on the number of patent applications. Lu and Tsai (2004) proposed a computer vision-based defect detection scheme for TFT-LCD technology inspections in manufacturing system. In addition, the competitive strategies of Taiwan's TFT-LCD industry (Hung, 2006), material properties of TFT-LCD waste glass

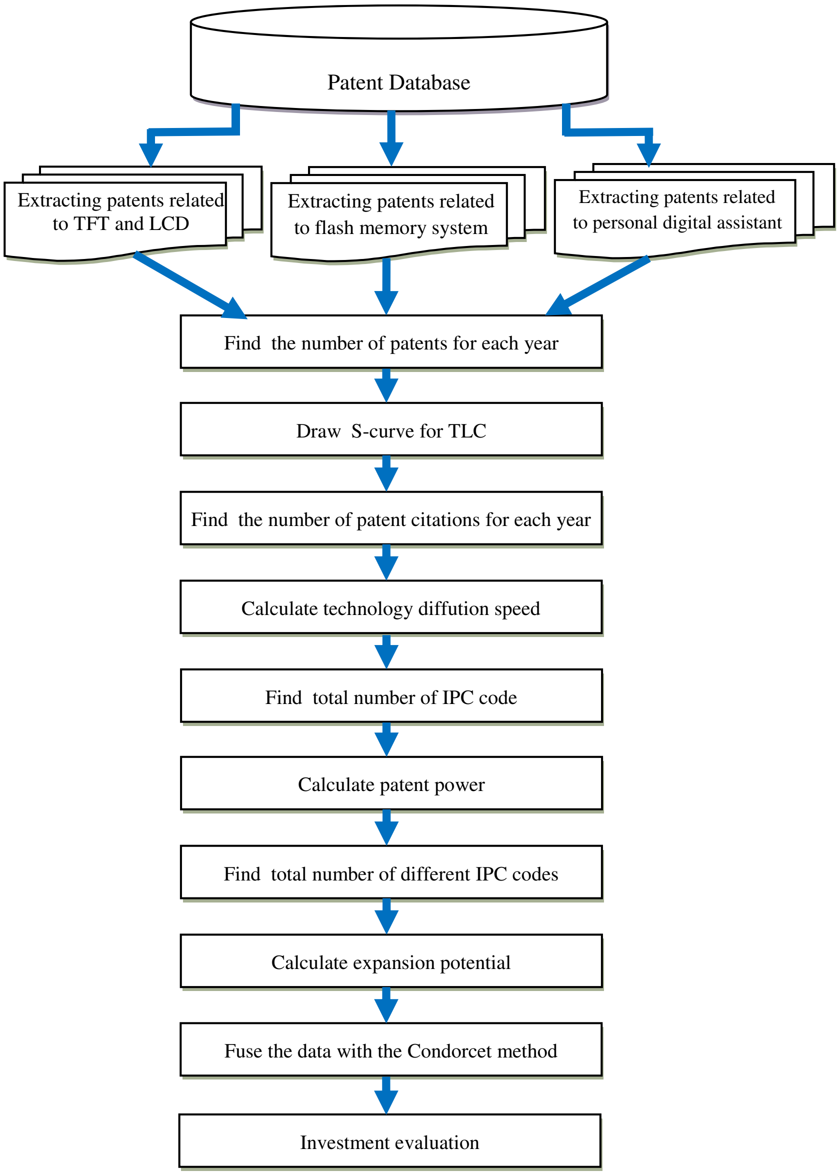

Fig. 3. Overview of the proposed methodology.

(Lin, 2007), knowledge flows and innovation capability within and across Taiwan's top five major players in the TFT-LCD industry (Hu, 2008), analysis of TFT-LCD industry success factors (Wang et al., 2011), and technological innovation capabilities in the TFT-LCD industry (Hu, 2012) are also examined in the literature.

2.3.2. Flash memory system

Flash memory system is one of the portable data storage technologies. It has no moving parts, greater reliability, less power consumption, and faster performance (Wildstrom, 2007). Nowadays, this technology is widely adopted in embedded applications (Chung et al., 2006). Therefore, the flash memory market continues to rise (Yinug, 2007). "Most of the existing research on flash memory has focused on cell research, write/erase reduction, and the mapping algorithm for cell data, etc." (Kim et al., 2014). Herein, a review of these researches would deviate from the aim of this paper. Therefore, only patent based studies are examined here. Daim et al. (2008), forecasted the future of two data storage technologies, namely hard disk drive and flash memory based on the numbers of publication patents. They found that the cumulative patents have continued to increase for these two technologies. Choi and Park (2009) proposed an approach to identify patent development paths from a large patent citation network to analyze flash memory technology. The search keyword used for patent analysis was 'flash memory system' in their study.

2.3.3. Personal digital assistant

A personal digital assistant (PDA) is a mobile device, which is going to become more popular in worker's daily jobs because it allows workers to plan and organize daily jobs and access information that they require in personal life. PDA technology helps users communicate more effectively and efficiently and helps them in managing all their information needs (Bayus et al., 1997). Chen et al. (2007) expressed that PDA applications which exploit wireless communication are appropriate for use in clinical practice. Golden and Geisler (2007) examined the usage and interpretation of PDA technology by workers as a boundary management resource. Lee et al. (2009) conducted a patent analysis for the case of PDA technology to develop keyword-based patent maps and apply them to the idea generation phase of new technology creation using 141 PDA-related patent documents. The use of PDA technology in health care systems is also examined from different aspects by Johnson (2008), Garrity and Emam (2006), and Carroll and Christakis (2004).

Although there are some studies conducted on thin film transistor-liquid crystal display, flash memory system, and personal digital assistant technologies, there is no study that compares them with respect to future technology success. Existing researches focused on only one of these technologies at a time. To address the needs in technology forecasting, technology life cycle, diffusion speed, patent power, and expansion potential are considered. This study also differs from previous works in that it considers multiple indicators composed of the four key investment factors together.

3. The proposed method

The proposed method prioritizes technologies that are awaiting financial investment incentives. The proposed method uses the TF indicators to compute technology success and systematically prioritize the available investment opportunities and therefore, it ranks technologies with respect to their sustainability in the future. The proposed method consists of nine steps as presented in Fig. 2. In Step 1, the data related to the technologies considered in this research is extracted from the patent database. In fact, any suitable patent database could be used in Step 1. Numerous researchers use the United States Patent and Trademark Office (USPTO) database in the literature due to the fact that USPTO receives a vast amount of patent applications each year. Therefore, analysis of these patents may lead to generalizable results. In Step 2, a TLC (S-curve) is constructed by using the cumulative number of patents issued in each year. The cumulative number of patents indicates attractiveness and change of the technology in time. Following that, in Step 3 the question is posed, "Are all of the investment candidates at their growth stage in the TLC?" If the answer to the question in Step 3 is no, the method continues to Step 4 where technologies that are not at the growth stage are deleted and the remaining technologies are considered candidates. It is expected that all technologies should be at growth stage in their TLC to avoid insufficient investment. If the outcome of the

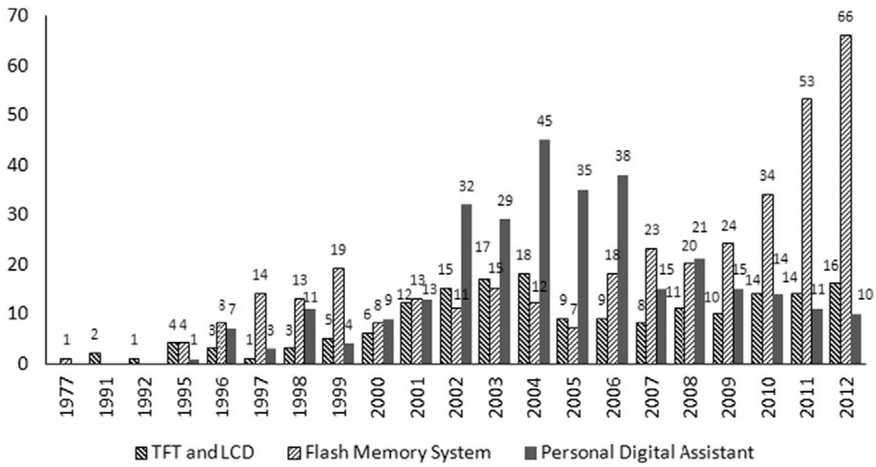

Fig. 4. The number of patents for TFT-LCD, flash memory system and personal digital assistant technologies.

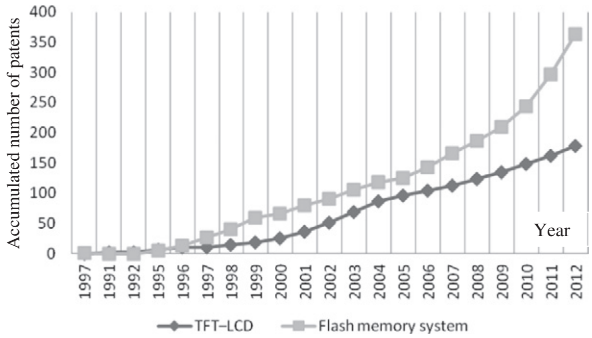

Fig. 5. S-curves of TFT-LCD and flash memory system technologies.

answer in Step 3 is yes, then the method leads to Step 5 where the technology diffusion speed is computed using expression (1). In Step 6, patent power is computed from expression (2). In Step 7, the total number of different IPC codes as a measurement of expansion potential is computed. Steps 6 and 7 also indicate commercialization potential of the technology indirectly. If the values produced by Steps 6 and 7 are high, there is a high possibility that marketing potential of the technology in the future will be high. It is necessary to combine the results of Steps 3, 5, 6 and 7 to rank candidate technologies. The Condorcet method in Step 8 combines and prioritizes the results of these steps. Finally, the technologies are evaluated and ranked in Step 9.

4. Application of the proposed method

The proposed method is illustrated using three separate technologies: thin film transistor-liquid crystal display (TFT-LCD) technology, flash memory system technology, and personal digital assistant technology.

4.1. Patent analysis

In Step 1, patents related to TFT-LCD technology, flash memory system technology, and personal digital assistant technology are retrieved using AcclaimIP software (www.acclaimip.com), formerly known as CobaltIP software (www.cobaltip.com). The published patents related to these three technologies were provided by the databank USPT that contains all US granted patents. AcclaimIP software provides different options for patent research and analysis. The users can research patents by titles, abstracts, country, IPC class and so on. The analysis can be conducted in different patent databases such as European Patent Office (EPO), USPTO, World Intellectual Property Organization (WIPO) and Japan Patent Office (JPO). The keyword "equations" (research queries) were used to collect patent documents for each technology, and to retrieve the total number of patents, patent citation numbers, the total number of IPC classes, and the number of different IPC classes for each technology (see Table 2). The research terms can be conducted with just the titles of the patents (e.g., Jun, 2011a,b; Wu et al., 2010), or with both titles and abstracts of the patents (e.g., Tseng et al., 2011; Lee et al., 2015). In this study, the research terms are in the titles of the patents, i.e., patents that include the research queries in their titles are considered for each technology. All granted patents published in USPTO until November 13, 2012, when this research was conducted, are considered in this paper. In addition, "Word Stemming" feature that is available in the AcclaimIP software is not used to avoid patents which include variations related to word(s) included in research queries. The results of the computational search are summarized in Table 2. The proposed methodology is illustrated in Fig. 3.

Fig. 4 illustrates the number of patents in different years for TFT-LCD, flash memory system and personal digital assistant technologies. Fig. 4 demonstrates that even though TFT-LCD technology was developed prior to 2001, it led to new patents in the same year, which points toward its significance. Similarly, the number of patents for flash memory technology increased in 2006 and in subsequent years. The number of patents in personal digital assistant technology increased in 2001. Between 2001 and 2007, the number of patents related to

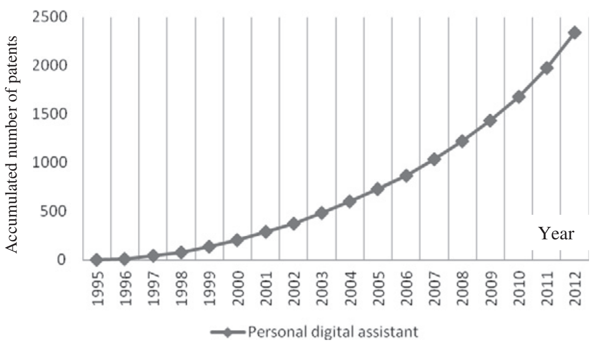

Fig. 6. S-curve for personal digital assistant technology.

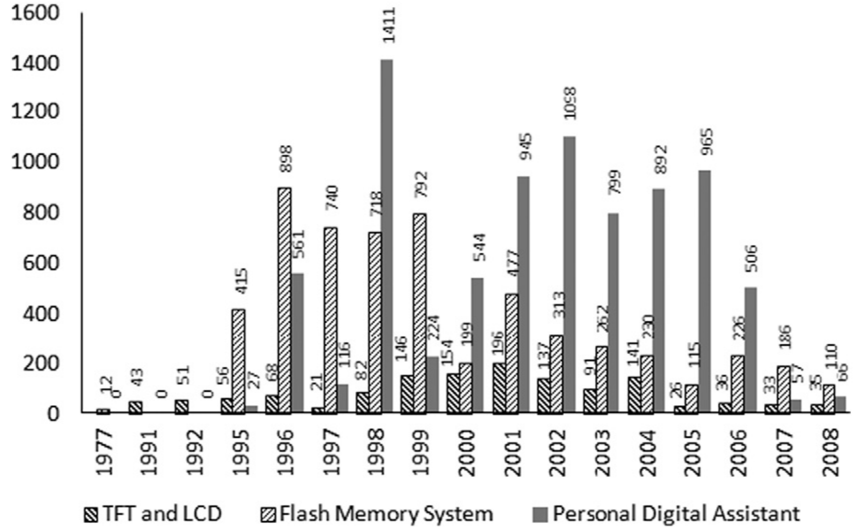

Fig. 7. The number of citations for TFT-LCD, flash memory system and personal digital assistant technologies.

personal digital assistant technology remained high, with a peak in 2004. Fig. 5 presents the S-curves for TFT-LCD technology and flash memory system technology. Fig. 6 also illustrates the S-curve for personal digital assistant technology. As illustrated in Figs. 5 and 6, these three technologies are at the growth stage of their technology life cycle because the cumulative number of patents of these technologies has not begun to stabilize and decline yet. Based on these figures, these

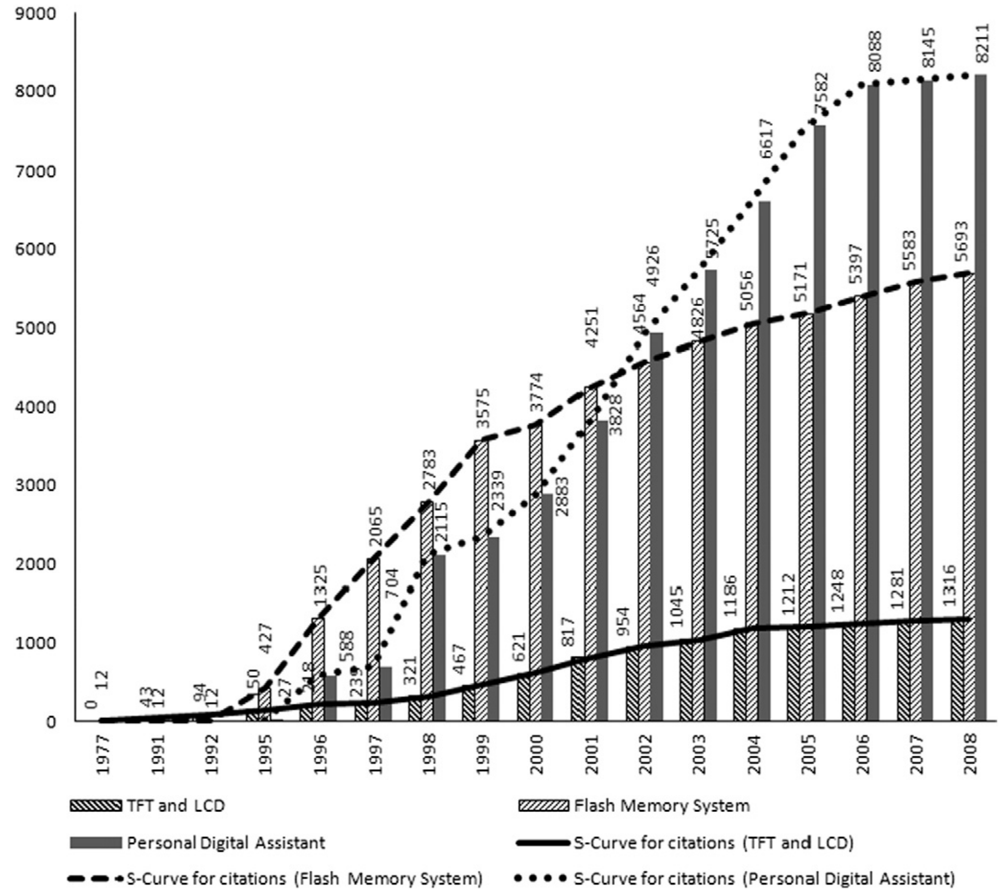

Fig. 8. The cumulative number of citations and S-curve for citations of TFT-LCD and flash memory system technologies.

Table 3
Technology diffusion speed.

Technology	Total # of patents	Total # of patent citations	Diffusion speed
TFT-LCD	124	1316	10.61
Flash memory system	183	5693	31.11
Personal digital assistant	261	8211	31.46

technologies have not reached the saturation stage. Therefore, these three technologies should be of equal priority with respect to TLC criteria. The answer to the question in Step 3 of the proposed method (see Fig. 3) is yes and the method continues to Step 5 in this application.

Fig. 7 illustrates the number of citations for TFT-LCD technology, flash memory system technology, and personal digital assistant technology. It should be noted that all patents considered in this paper for measuring technology diffusion were issued before November 13, 2008. According to Gay et al. (2005), on average the first patent citation occurs with a four year delay. Therefore, the total number of patents considered for measuring technology diffusion speed is less than the total number of retrieved patents considered for TLC.

Fig. 8 illustrates the cumulative number of citations for TFT-LCD technology, flash memory system technology, and personal digital assistant technology. As can be seen from this figure, the cumulative number of patent citations for each investment candidate follows the S-curve shown in Fig. 1. Table 3 reports the technology diffusion speed of each investment. As can also be seen from Table 3, personal digital assistant technology has the highest diffusion speed. The investments are ranked as personal digital assistant technology > flash memory system technology > TFT-LCD based technology when evaluating diffusion speed. This means that personal digital assistant technology has the highest diffusion speed among the alternatives. It should be noted that the values given in Tables 3 and 7 do not match exactly as given in Table 2 because the total number of considered patents for measuring each criterion is different.

IPC classes and their frequencies for TFT-LCD technology, flash memory system technology, and personal digital assistant technology are provided in Tables 4, 5 and 6, respectively. Comparison of these three investment candidates with respect to technology scope indicators (namely patent power and expansion potential) are summarized in Table 7. As can be seen from Table 7, the total number of considered patents for measuring technology scope is the same as the number of patents that are considered for TLC. IPC codes and their definitions are provided at the WIPO webpage (http://web2.wipo.int/ipcpub/#refresh=page).

Based on the data in Table 7, TFT-LCD technology has the highest priority, personal digital assistant technology comes second, and flash memory system technology is third with rspect to patent power criteria. On the other hand, the expansion potential of personal digital assistant technology is quite high when compared to TFT-LCD technology and flash memory technology, which have an equal expansion potential (value of 21). Therefore, the prioritization of technology is as in the following:

Patent power: TFT-LCD > personal digital assistant > flash memory system
Expansion potential: personal digital assistant > TFT-LCD = flash memory system

4.2. The Condorcet method

The results from the previous section are summarized in Table 8. As can be seen from this table, TFT-LCD and flash memory technologies have the same ranking with respect to the expansion potential criterion as both have the same expansion potential value (21). Three technologies also have the same ranking with respect to TLC.

The Condorcet method is applied to fuse together the different candidate technologies.

Each technology is considered a candidate and the result of each criterion is considered a vote in the method. Then, pairwise comparisons are performed to find the total number of

Table 4
The number of IPC classes for patents related to TFT-LCD technology.

No.	A	B	No.	A	B	No.	A	B	No.	A	B
1	G02F	123	6	G09F	10	11	G03F	3	16	G01N	1
2	H01L	76	7	H04N	8	12	H03F	2	17	G03B	1
3	G09G	43	8	G06F	5	13	B23B	1	18	G06K	1
4	G02B	11	9	G11C	4	14	C08G	1	19	G06T	1
5	G01R	10	10	H03K	4	15	F21V	1	20	H02M	1
									21	H03M	1
									Total 308		

A: IPC code. B: Frequency.

Table 5
The number of IPC class for patents related to flash memory system technology.

No.	A	B	No.	A	B	No.	A	B	No.	A	B
1	G06F	237	6	H04L	4	11	A43C	1	16	G10L	1
2	G11C	174	7	H05K	4	12	F02D	1	17	H01R	2
3	H01L	28	8	G11B	2	13	F16H	1	18	H03K	1
4	G06K	3	9	H03M	2	14	G05B	1	19	H04M	1
5	G01R	3	10	H04B	2	15	G08C	1	20	H04Q	1
									21	H05B	1
									Total 471		

A: IPC code. B: Frequency.

Table 6
The number of IPC classes for patents related to personal digital assistant technology.

No.	A	B	No.	A	B	No.	A	B	No.	A	B
1	G06F	153	14	H05K	7	27	G09F	2	40	B06B	1
2	H04M	49	15	G01S	7	28	G06T	2	41	F21Y	1
3	G06K	26	16	H04R	7	29	A62C	1	42	G07G	1
4	H04B	20	17	H04W	6	30	F16M	1	43	B65G	1
5	B41J	18	18	A45C	5	31	G06G	1	44	G07F	1
6	H04L	17	19	G02F	4	32	H05B	1	45	H01Q	1
7	H04N	15	20	G09B	3	33	G07C	1	46	B65D	1
8	G06Q	12	21	A61B	3	34	G07D	1	47	H03J	1
9	G02B	10	22	H01R	3	35	G08C	1	48	G01R	1
10	G01C	9	23	G08G	2	36	B60R	1	49	G05B	1
11	H01H	8	24	H02J	2	37	G11C	1	50	G05D	1
12	H04Q	8	25	F21V	2	38	F16B	1	51	F24F	1
13	G09G	7	26	G10L	2	39	H01M	1	52	G05D	1
									Total 433		

A: IPC code. B: Frequency.

Table 7
Patent power and expansion potential.

Technology	Total # of IPC classes (A)	Total # of considered patents (B)	Patent power (A/B)	Expansion potential
TFT-LCD	308	178	1.73	21
Flash memory system	471	363	1.3	21
Personal digital assistant	433	313	1.38	52

wins, losses, and ties for each technology. Each complimentary pair is compared to the others to assign one point in the "Win" column for winner, one point in "Lose" column for loser and one point for a tie based on the result of each comparison. The Condorcet method can be utilized in the presence of at least two criteria and two alternatives. An example application of the Condorcet method is shown in Nuray and Can (2006) in the presence of three alternatives and five criteria.

Based on the data in Table 8, a pairwise comparison and the corresponding points for TFT-LCD, flash memory and personal digital assistant technologies are provided in Tables 9 and 10. As can be seen from Table 10, the win score for personal digital assistant technology is higher than that of TFT-LCD and flash memory technologies. Therefore, the investment priority for personal digital assistant technology should be higher than that of TFT-LCD and flash memory technologies. The win, lose and tie scores are the same for both TFT-LCD and flash memory technologies. The final ranking is c > a = c. This means that personal digital assistant technology should be supported more than TFT-LCD and flash memory technologies.

5. Conclusion and discussion

Forecasting the future success of technology is complex due to the unstable market conditions and limited information. Investors cannot easily see one step ahead in this condition for their technologies that are invested in. Therefore, a new approach is proposed to forecast the future technology success based on patent data which has been extensively used for technology forecasting in the literature. The proposed approach offers an opportunity to track the change of the technology over time for investment. This study addressed three issues in technology dissemination: (i) appropriate stage of the technology life cycle for investment, (ii) diffusion potential of the technology of interest, and (iii) scope of the technology of interest. Multi criteria affect technology success in the future. This study also differs from previous works in that it considers multiple indicators composed of the four key investment factors together. Four criteria, technology life cycle, technology diffusion speed, patent power, and patent expansion were considered in this paper. In addition, previous studies generally focused on TLC of investment alternatives at a time. Proposed methods in the literature did not use these four criteria together. Addressing these issues prior to investment resulted in numerous benefits. For example, the investor can foresee opportunities and threats related to his/her investment and can also seize the opportunity to revise his/her investment project(s) and the government may decide whether to support the investor(s). An investment project which has high priority can be supported more and should gain more incentives than others which have less priority in the constructed investment incentive system in a country. In addition, an investment project which has high priority indicates technology success as well as its possible direction in the future. Technology spillover among different technology classes can be pursued as well. Patents were applied for technology forecasting using AcclaimIP software. However, the most difficult task in the proposed approach was to obtain data for analysis which was downloaded from a patent database.

A new method for technology forecasting using four criteria for patent analysis and the Condorcet method for data fusion was proposed. The proposed method readily facilitates a prioritization of possible investments. The utility of the proposed method was demonstrated with a comparative study of three technologies: TFT-LCD technology, flash memory system technology, and personal digital assistant technology. The researches in the literature focused on only one of these technologies at a time. There is no study that compares them with respect to future technology success. The proposed method ranked these technologies in terms of their investment potential. Personal digital assistant technology emerged ahead of the other two technologies. The results from the case study showed that the proposed approach can be utilized to forecast technology success based on patent data.

The proposed method provides answers to questions such as: which technologies are appropriate for investment, and what is the prioritization among technologies? Distinction among technologies with respect to future technology success can be easily performed through the proposed method. Therefore, successful investment alternative(s) can be selected among available investment proposals. Decision makers, managers or researchers can use the proposed method to prioritize investment projects with respect to future technology success.

There are some limitations to this study. First, patent data was retrieved from the patent database by using the research

Table 8
Ranking of investments with respect to criteria.

Criteria	Rank
TLC stage	a = b = c
Technology diffusion speed	c > b > a
Patent power	a > c > b
Expansion potential	c > a = b

a: TFT-LCD technology. b: Flash memory technology.
c: Personal digital assistant technology.

Table 9
Pairwise comparison.

	a	b	c
a	–	(1, 1, 2)	(1, 2, 1)
b	(1, 1, 2)	–	(0, 3, 1)
c	(2, 1 ,1)	(3, 0, 1)	–

a: TFT-LCD technology. b: Flash memory technology.
c: Personal digital assistant technology.

Table 10
Assigned points.

	Win	Lose	Tie
a	0	1	1
b	0	1	1
c	2	0	0

a: TFT-LCD technology. b: Flash memory technology.
c: Personal digital assistant technology.

terms with just the titles of the patents. The research that uses the research terms in titles, abstracts, keywords and claims of the patents can be performed to extend the results reported in this paper. Second, the results of this paper are limited only to patent data. In addition to patent data, publication data, which can be obtained from the Science Citation Index and Compendex, can be also taken into account in the technology forecasting process. Third, generating the number of citations and IPC codes for each patent is not easy to do. There is a need for software computing of the number of citations and IPC codes. Fourth, there are many factors affecting investment decisions such as payback period of the investment, break-even point for the investment, marketing success of the investment, location, raw material proximity, labor availability, etc. These factors can be also taken into account in the technology forecasting process for evaluation of investments. Fifth, the proposed method assumes that investment is beneficial and productive for the investor, if it takes place in the growth stage of TLC and all conclusions therefore are subject to this assumption.

In future research, the Bass diffusion model will be used to measure technology diffusion potential. Additionally, a better use of IPC patent classes will be studied in future research. As a high risk investment may take place at the end of the initiation stage, the fuzziness between the end of the initiation stage and the beginning of the growth stage will be examined with fuzzy logic. Marketing success of technology can also be forecasted. Export potential, domestic market potential and technology novelty can be taken into account as evaluation criteria for forecasting marketing success in future studies. The technologies, which are in the scope of the technology of interest, falling into radical and gradual technologies should be considered in future research. Furthermore, the innovation potential of technologies can be considered in the evaluation process because patent data also provides knowledge about innovation (especially incremental innovation). Finally, Gompertz and Pearl growth curves can be applied to forecast TLC stages of the technologies.

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