ABSTRACT

GARLAND, GENEVIEVE MARIE. Technology Forecasting (TF) using Hybrid Tech Mining, TRIZ TF for Research and Development Planning: Forecast for Nonwovens Air Filtration Media. (Under the co-direction of Dr. Timothy G. Clapp and Dr. William Oxenham).

The objectives of this research were to identify the type of information found in tech mining and TRIZ TF forecasts and determine if combining tech mining and TRIZ TF forecast results offers improvements over either single method. The research was conducted in two phases. The first phase was to develop the hybrid, tech mining TRIZ TF methodology. In this phase a literature review was conducted on both methods then they were reviewed and combined to maximize the value of the hybrid forecast and minimize weaknesses in either method. In the second phase tech mining and TRIZ TF forecasts were conducted using data from 1950-2000 and forecasted for 2005 and 2010. To develop the forecasts nonwoven air filtration media was used as the forecasting topic. The two TF methodologies and hybrid forecast were described in detail and the results were evaluated for ease of use, time, value of information and accuracy. This research aimed to combine two methods not currently used in combination and compared the individual forecasts to the hybrid forecast. In addition this study contributed to the field of TF by offering an experimental, transparent approach for creating each forecast using the individual methods along with a systematic method for evaluating the forecasts.

Technology Forecasting (TF) using Hybrid Tech Mining, TRIZ TF for Research and Development Planning: Forecast for Nonwovens Air Filtration Media

by
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BIOGRAPHY

Genevieve Garland was born in Atlanta, GA but spent most of her life in North Carolina. She received her Bachelor of Science degree from North Carolina State University in Textile and Apparel Management where she was awarded Outstanding Apparel Student of the Year Award from the American Apparel and Footwear Association (AAFA). After completing her undergraduate degree she received a graduate assistantship from the College of Textiles at North Carolina State University and earned a Master of Science degree in Textiles. Genevieve was the International Textile and Apparel Association (ITAA) graduate research paper competition winner in 2003. Upon completion of her M.S. degree, Genevieve took a position as an Instructor at the College of Textiles in the Textile and Apparel, Technology and Management department in 2003. While working as an Instructor, Genevieve began to also work as a consultant to TC^2 in Cary, NC and Manitoba Fashion Institute in Winnipeg, Canada. In 2006, she took a position as a Product Development Specialist with TC^2, but continued as an Adjunct Lecturer at North Carolina State University. Genevieve Garland currently is Director of Partnership and Innovation for The Nonwovens Institute (NWI) at North Carolina State University. She joined the Institute in February, 2008 where she is responsible for marketing the Institute; industry, government and academic partnership and business development; assisting in technology transfer; teaching; market intelligence research; technology forecasting and integration of research and education. While working Genevieve began pursuing a doctorate in Textile Technology Management and completed the requirements for her degree in the spring of 2013.

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CHAPTER 1: Introduction

"Corporations everywhere are engaged in a new products war" (Cooper, Winning at New Products, 2001, p. 1). Continually introducing new products into the market is a key strategy companies use to gain and sustain a competitive advantage. A major problem for companies using this strategy is 35%-45% of the new products never reach the market (Cooper). A potential contributor to the failure rate is the lack of innovation in the projects and products companies select (Cooper). Most new products developed are results of cost reductions, improvements, extensions, or variations of current products while true breakthroughs account for only 10% of new products (Cooper). Experts view successful product innovation from two perspectives; 1) having the right innovation process 2) selecting the right projects (Cooper, 1999). Technology forecasting (TF) can aid decision makers in selecting the right projects by providing them with insight into how technology may change. Strategically selecting and combining technology forecasting techniques like tech mining and TRIZ TF may offer improvements over current methods. Tech mining utilizes the large volumes of digital information available to recognize possible development trends while TRIZ TF goes a step beyond traditional methods by extending into idea generation and providing a long term vision of the future. Advances in technology are drivers of innovation and successful technology management can lead to superior developments and ultimately superior new products.

Purpose of Research

The objectives of this research were to identify the type of information found in tech mining and TRIZ TF forecasts and determine if combining tech mining and TRIZ TF forecast results offers improvements over either single method. This research aimed to combine two methods not currently used in combination and evaluate the resulting forecasts. Tech mining was used as the foundation method due to its acceptance in the TF community and elements of TRIZ TF were integrated into the forecast. The premise behind the development of the hybrid forecast is that combining the forecasts will improve the resulting forecast. The results of the research will expand the academic research on combining TF methods and also provide a method for evaluation of TF methods.

Research Questions

RQ1: What should the methodology be for a hybrid TF using tech mining and TRIZ TF?

RQ2: What type of information is obtained from the individual and hybrid TF forecasts?

RQ3: Does the hybrid forecast offer improvements over either single method?

Significance of Study

The literature reveals that TF methods are often combined with the assumption the combination forecast offers advantages over a single method but this hypothesis has not been validated. This research aimed to combine two methods not currently used in combination and compare the individual methods to the hybrid forecast. In addition this study will contribute to the field of TF by offering an experimental, transparent approach for creating each forecast using the individual methods along with a systematic method for evaluating the forecasts.

CHAPTER 2: Literature Review

Technology Forecasting has commonality with the broader field of Forecasting but also faces unique challenges. TF is the "prediction of the future characteristics of useful machines, procedures, or techniques," (Martino, 1993, p. 1). "The greatest benefit of forecasting lies in its use as guidance for the activities of large organizations," (Lenz, 1969, p. v). The forecaster is not required to understand the science of how a future technology will accomplish the unforeseen advancement; the forecaster's job is to know what will happen and when (Martino, 1969). Typical demand or consumption forecasts have a large amount of historical data as a basis for developing the forecast. When developing a forecast for an existing technology TF is also able to utilize historical data, but often a technology forecast is attempting to predict when and what will be the next technology innovation. Forecasting breakthrough technologies is challenging because they often disrupt previous trends and when in the concept stage limited to no data is available to develop the forecast (Mackay & Metcalfe, 2002). TF is not an exact science but with or without formal forecasts organizations are making decisions everyday based on their vision of the future. TF provides a systematic approach to looking at the possible futures and provides decision makers with information that helps them anticipate, drive and plan for the technology change that leads to breakthrough technologies and products.

TF theories, methods, and applications are examined in a variety of disciplines: technology management, futures research, engineering management, technology innovation and entrepreneurship, and various scientific and engineering disciplines (Roberts, 2004). Today a majority of the research on TF is found in the discipline of futures research. Futures research is defined by Glenn and Gordon (2003) as a multi-disciplinary field that studies change in all aspects of life including economics, society, and technology and the possible futures that will have a significant impact over many years.

Elements of a Technology Forecast

A technology forecast typically has four elements: 1) qualitative description of the technology being forecast; forecasting question 2) identification of characteristics being forecasted; ideally quantifiable 3) a statement of time associated with forecast 4) a statement of probability associated with forecast (Martino, 1993; Twiss, 1992). All of the elements are important to the forecast; unfortunately, a forecaster does not usually have an equal amount of information or quality of information for each element (Martino, 1993). Typically accuracy in one element means less accuracy in another (Martino). Regardless of accuracy all four elements are essential to the forecast; and, if any are missing some level of vagueness is brought the forecast (Twiss, 1992).

The identification of the forecasting question or problem is central to the quality of the resulting forecast (Twiss, 1992). If the forecaster is not asking the right questions or is unaware of developing areas, the forecast may not hold value to the decision maker(s) (Twiss). A forecaster may perform a preliminary forecast around a broad topic area to better understand how to form the forecasting question (Twiss).

The objective of TF is to understand and predict how technology changes over time, so a forecast must include some method for measuring the performance of the technology. In order to determine a measurement method, the parameters associated with the technology must be identified. Twiss (1992) states the market is the driving force for technology;

therefore, he suggests a sequence for selecting the parameters: 1) identify market attribute required by user in the total system 2) determine the technical parameter(s) that represent the attribute 3) take into consideration technology, economic, social or political changes that may affect the system. Martino (1993) identifies two types of parameters: 1) functional[1]: a measurement that directly relates to the user's need and satisfaction 2) technical: a measurement of performance properties which are often combined to address a functional need. Martino also states the forecast's objective should be taken into consideration when selecting functional versus technical parameters. Martino suggests technical parameters may be more suitable for forecasting research and development planning while functional parameters may be more suitable for market planning.

Along with evaluating how technology changes over time TF's purpose is to relate this change to a timeframe. Relating technology advancement against time is a challenge because there is no causal relationship between technology advancement and time (Twiss, 1992). In TF how far in the future the forecast is aiming (long-term, 30 years versus short-term, 5yrs) has a significant impact on forecast accuracy (Porter et al., 1991). Typically a shorter timeframe will be more accurate and experts prefer the most recent forecast regardless of the quality (Ascher, 1978; Porter et al.).

The last element is the level of confidence associated with the forecast or the probability the forecast is correct. The future is uncertain so there will always be some level of uncertainty in TF (Martino, 1993; Porter et al., 1991; Twiss, 1992). The probability can

[1] Twiss uses the term market attribute in place of functional parameter and points out several technologies with their associated technical parameters may contribute to a single market attribute (Twiss, 1992).

be for the entire forecast, a specific level of technical performance, a specific level of functional performance, a certain level of performance by a certain time, or the entire forecast achieved by a certain time (Martino, 1993). It is easier to associate a probability to forecasting methods that are mathematically and/or time-series based. Other methods require some level of judgment from the forecaster to be able to determine the level of confidence (Porter et al., 1991). One approach to the latter is to evaluate the accuracy of similar historical forecasts (Porter, et al). According to Porter et al. a forecast that points at a single future is unlikely and not credible. They suggests forecasters give the decision maker a range of possible futures and specify the likelihood one of the futures is correct (Porter, et al). In addition a forecaster should consider possible future economic, social, and political events that may cause a disruption in the system (Twiss, 1992). The timing of these events can be identified but cannot be forecasted, but the events should be identified and the impacts considered (Twiss).

Principles for a good forecast

In addition to the four elements mentioned previously a “good” forecast adheres to several key principles. First, the forecast must be reliable and valuable to the decision maker (Porter et al., 1991). The forecast should also be formed using the best available information (Porter et al., 1991). When selecting information that will be the foundation of a forecast the data should be measureable, a true representation of the performance of the technology, pertinent for measuring a range of technology approaches, readily available, and consistent in the stage of development for the range of technology approaches (Martino, 1993) . The forecasting method is also an important aspect of a “good” forecast. The methods employed to process and evaluate the information should be “clearly described, methodologically sound, replicable, and logically consistent,” Porter et al., 1991, p. 52). Complex forecasting methods may hender the ability to perform a repeatable forecasting process often enough to validate assumptions and results (Ascher, 1978). Lastly, all assumptions associated with the forecast should be stated and any information used to support the assumptions should be supplied (Porter et al.).

Evaluating Forecasts

The best place to begin the discussion of TF evaluation is with the two types of evaluation. The first type, and most commonly used in TF, is summative (Porter & Rossini, Evaluation Design for Technology Assessments, 1977; Scriven, 1967). A summative evaluation takes place after the forecast is completed and evaluates the forecast based on validity and utility (Porter & Rossini, 1977; Porter et al., 1991). The second type of evaluation is formative. A formative evaluation is done during the forecasting process (Porter & Rossini, Evaluation Design for Technology Assessments, 1977). Porter et al., (1991) says formative evaluations are usually informal and may be something as simple as providing decision-makers early drafts of the forecast for review.

Summative Evaluation

There are a limited number of formal evaluations of technology forecasts and all found in the literature were summative evaluations of collections of historical forecasts (Ascher, 1978; Schnaars, 1989; Wise, 1976). The primary evaluation criterion used in evaluations is validity. These evaluations do not adhere to a common methodology for forecast selection or assessment but all typically result in a list of common flaws found in the historical forecasts. Schnaars (1989) suggests the limited review of previous forecasts for accuracy is because "forecasters are afraid that by looking back they will be turned into the business equivalent of biblical pillars of salt" (Schnaars, 1989, p. 2). This statement highlights one of the major challenges for technology forecasters, evaluation.

Formative Evaluation

There were no formal formative evaluations of actual technology forecasts found in the literature. Martino (1993) developed the *Interrogation Model* to evaluate a forecast's usefulness to a decision maker. The *Interrogation Model* is a four step process consisting of a series of questions asked about the forecast. Although Martino developed the model to evaluate a completed forecast, this model can be used during the development of the forecast to improve the forecast's reliablity and value (Porter et al., 1991). The model examines a forecast according to need, underlying cause, relevance, and reliability (Martino, 1993, pp. 328-337). Armstrong (2001) suggests a forecast should be evaluated based on both its inputs and outputs. Armstrong developed a forecasting standards checklist for the field of forecasting, but the checklist may be useful for a technology forecast depending on the TF method employed. (Armstrong, 2001, p. 465)

Evaluation Criterion

Experts differ on the criterion for evaluating a forecast. Some believe accuracy is the most important (Ascher, 1978; Schnaars, 1989). Others believe a forecast assessment shouldn't be based on accuracy alone (Armstrong, 2001; Martino, 1993; Porter et al., 1991). Technology forecasts will always be flawed and the true accuracy of the forecast is not known at the time it is being used by the decision maker; for that reason, evaluation should include the usefulness of the forecast to the decision maker (Martino, 1993). Porter et al (1991) states, it is "unfair to gauge a forecast just by whether it came true or not [because] forecasts are conditional, and a forecast that induced an organization to avoid a predicted negative outcome by altering key factors must be judged a rousing success" (Porter et al. 1991, p. 383). The field of technology forecasting is based on laws, patterns and logical relationships applied in the form of forecasting methods. These methods link current and past information to possible futures; therefore, the method itself should be evaluated when assessing a forecast (Martino, 1993). Lastly the data used to develop the forecast plays an important role in the quality of a forecast (Martino).

Classification of Technology Forecasting Methods

A review of literature reveals a large number of TF methods and a variety of approaches to classifying the methods. Most experts agree the techniques may be grouped into two opposing theoretical views of how technology develops, normative or exploratory. The normative position is, technology develops from a need in the environment and has a social purpose (Ayres, Technological Forecasting and Long-Range Planning, 1969). A normative forecast begins with a future goal or perceived need and forecasts how to reach the objective (Porter, et al., 2004; Frick, 1974). The exploratory position states technology evolves naturally with a life of its own (Ayres, 1969). An exploratory forecast relies on data from the past and present to determine what will happen at some future point in time (Ayres). Frick (1974) illustrates the difference between normative and explorative forecasts as shown in *Figure 1*. He describes normative forecasting as "pulling objectives" and exploratory as "pushing opportunities" (Frick). Literature states that some methods can be used for both normative and exploratory forecasting (Porter, et al., 2004). The literature also describes methods by the type of information the forecast provides; qualitative forecasts provide descriptive results and quantitative forecasts provide numerical results.

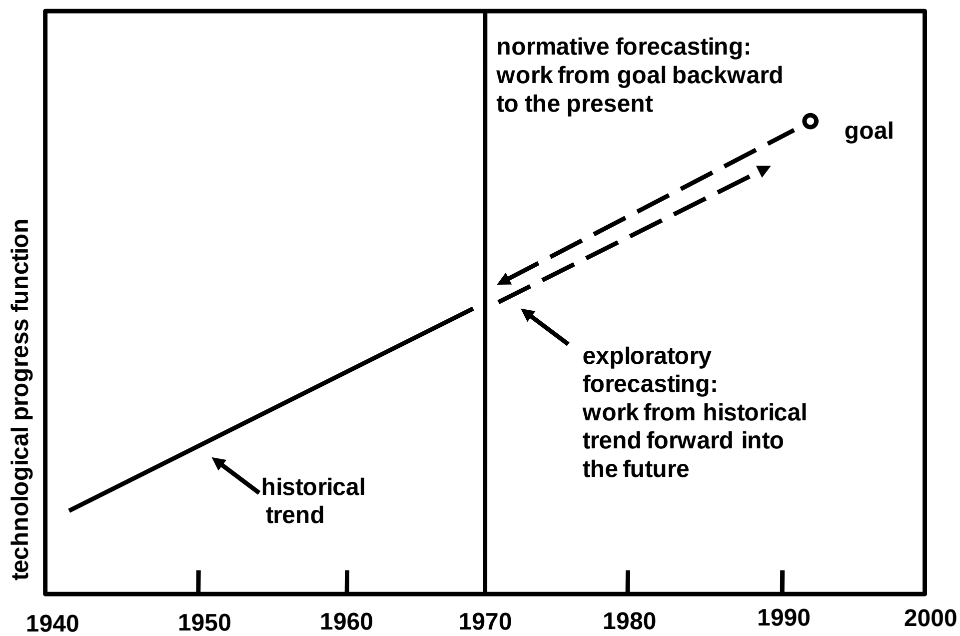

Figure 1. Normative vs. exploratory forecasting

Note. From "Operations Research Technological Forecasting," by R. Frick, 1974, *Air University Revew*, May-June. Retrieved from *Air and Space Power Journal*on October 1, 2008 http://www.airpower.maxwell.af.mil/airchronicles/aureview/1974/may-jun/frick.html. Copyright 1974 by Air and Space Power Journal

Although there is not an agreed upon manner to categorizing forecasting methods, *Table 1* illustrates some of the systems found in the literature. Porter and Rossini, and Martino were early contributors to the field of TF and offered the first formal classification systems. Their approaches to classification have some common views but are not identical. Martino does not consider expert opinion as a separate category because he believes experts use past experiences to formulate their forecasts, so he places expert opinion within the extrapolation category (Martino). Porter and Rossini's monitoring family uses leading indicators to point to signals of technology change, but Martino does not include monitoring as a classification or discuss it as method in his book. Porter and Rossini and Martino use broad categories to describe technology forecasting techniques which differ from the classification methods proposed by Porter et al. (2004) and Gordon and Glenn (2003). These classification systems were developed for futures research which includes technology foresight, TF, and technology assessment (Porter, et al., 2004). Gordon and Glenn (2003) sort the techniques by the type of information the forecaster is looking for or area of use as shown in *Table 1*. Porter et al. (2004) groups the techniques into families that describe the nature of the forecasting technique. Both attempts to classify futures research are more intuitive and precise than earlier approaches to classify TF.

Table 1. Literature review of classification methods for technology forecasting methods

Author	Porter and Rossini (1987) Families	Martino (1993) Methods	Gordon and Glenn (2003) Grouping by Area of Use	Porter et al. (2004) Families
Field of Research	Technology Forecasting	Technology Forecasting	Futures Research	Futures Research
Method	Trend Extrapolation	Extrapolation	Collect judgments	Expert Opinion
	Monitoring	Leading Indicators	Forecast time series, and other quantitative measure	Statistical
	Expert Opinion	Causal	Understand the linkages between events, trends, and actions	Descriptive and matrices
	Modeling	Probabilistic	Determine a course of action in the presence of uncertainty	Modeling and Simulation
	Scenarios	Combinations	Portray alternate plausible futures	Scenarios
			Reach an understanding if the future is improving	Monitoring and Intelligence
			Track changes and assumptions	Trend Analyses
			Determine system stability	Valuing / Decision / Economic
			Combinations	Creativity

Note. From Glenn & Gordon, 2003; Martino, 1993; Porter, et al., 2004; Porter & Rossini, 1987
Information compiled into Table by author

Another approach to categorizing TF methods that should be mentioned is Vanston's five views of the future™ (Vanston, 2003). Illustrated in *Table 2*, Vanston developed a unique approach which categorizes techniques by the forecaster's perception of the future.

This method of organizing forecasting techniques is more intuitive and descriptive than the previous mentioned methods.

Table 2. Vanston's Five views of the future™

View	Description
Extrapolators	The future represents a logical extension of the past
Pattern Analysts	The future will mirror cycles and patterns from the past
Goal Analysts	The future is determined by decision makers and leaders
Count Punchers	The future is unpredictable so a range of possibilities should be identified and monitored
Intuitions	The future is a mixture of trends, random events, patterns, and impacted by decision makers and leaders

Note. From "Better Forecasts, Better Plans, Better Results," by J. Vanston, 2003, *Researh Technology Management*, 46 (1), 47-59. Copyright 2003 by Research Technology Management.
Information compiled into table by author.

Critical Review of Select Methods

The field of TF employs a magnitude of methods for calculating future activities. Porter et al. (2004) provides the most recent compilation of techniques for assessing the future. Porter's work indicates there are 52 techniques including methods for technology foresight, TF, and technology assessment (Porter, et al.). Many of the techniques are extensions or variations on older techniques; therefore, it's difficult to distinguish between what is a unique technique and what is simply a variation.

Among the large number of methods found, a select group was chosen for review. Some of the methods reviewed are fundamental to the field, such as: Delphi, extrapolation, and causal models. The last three methods are more recent additions to the field of study and seen as an area for future development. Through literature review TF methods were identified as normative, exploratory, quantitative, and qualitative. *Table 3* lists the techniques to be reviewed and the classification.

Table 3. Classification of technology forecasting methods for review

	Normative	Exploratory
Quantitative	TRIZ TF Roadmaps	Tech Mining Causal Models Extrapolation TRIZ TF Roadmaps
Qualitative	Delphi TRIZ TF Roadmaps	Tech Mining Delphi TRIZ TF Roadmaps

Note. Table created by author

Delphi/Expert Opinions

The Delphi method is an expert opinion forecasting technique developed from research conducted at RAND Corporation[2] during the 1960s. Expert opinion techniques are based on the theory that experts for the field of interest will have more reliable answers to questions than non-experts. Delphi studies provide qualitative results and can result in both normative and explorative forecasts.

overview.

Delphi studies survey groups of experts with the belief a consensus among experts will result in more accurate forecasts than if a single expert was questioned. (Glenn & Gordon) There are many disadvantages associated with surveying people in groups: misinformation; social pressure; groups move towards agreement which may not be the best forecast; the group can be swayed by repetitive arguments and dominating individuals; and the group may share a common bias. The Delphi method addresses these weaknesses by providing anonymity for participants, controlled feedback, iteration, and statistical responses. (Glenn & Gordon, 2003; Martino, 1993; Porter et. al, 1991)

One of the primary factors of success in a Delphi study is the selection of experts. Experts may be identified through literature searches; recommendations from academia, institutions, professional organizations, or other experts; and through advertisements. It is important to consider all competencies required to address the topic being forecast and

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[2] RAND Corporation is a nonprofit institution with the mission of improving policy and decision-making through research and science. RAND published the first Delphi study, *Report on a Long-Range Forecast* written by Theodore Gordon and Olaf Helmer in 1964. (RAND Corporation, 2008)

ensure the group consists of experts from each area. The number of experts for Delphi studies ranges from 15 to 35 people. The actual study is based around a central question which may be normative or exploratory in focus. The study takes the group through multiple rounds of questions and feedback where they eventually form a consensus. The process begins by asking the group to provide an opinion; the results are given back to the group in the form of a numerical range including averages or medians for numerical based questions or categories for open-ended questions; individuals at the extreme positions are then asked to provide reasoning for their answers; all responses including the line of reasoning for the extreme positions are returned to the group; all members are asked to reassess their answers; the process is repeated once more before preparing the results. (Glenn & Gordon, 2003)

advantages and disadvantages.

The Delphi method is a useful tool for synthesizing and collecting expert opinions and particularly advantageous when forecasting long-range developments, understanding impacts of breakthroughs, and when forecasts require judgment (Glenn & Gordon, 2003; Gordon, The Methods of Futures Research, 1992). Martino (1993 & 1999) describes three conditions where expert opinion is necessary: 1) no historical data exist (typically new technologies), 2) impact of external forces are more important than the factors that governed the technology to its current state and 3) when ethical or moral issues dominate the topic being forecast. The Delphi method has been used repeatedly in national studies, including: Japan, Germany, Korea, and England (Porter, 1999). It is thought to be the best and possibly only method to conduct these large scale forecasts (Martino, 2003).

Some experts simply prefer quantitative techniques to qualitative and feel the base theory of expert opinion techniques is flawed, so they view Delphi in an inferior light (Ayres, 1999). Contrary to popular thought, Delphi studies require a large amount of time, effort and money (Martino, 1993). Delphi studies also require a skilled forecaster with knowledge in group selection, questionnaire development, synthesizing responses, and providing feedback (Porte et. al, 1991; Twiss, 1992). The process of selecting experts is not covered adequately in literature and should be further refined (Helmer, 1999).

variations of Delphi.

The Delphi method can be administered several ways, for instance: survey in person, mail, email, computers in a central location, or online at various locations (Glenn & Gordon, 2003). A recent attempt to improve the Delphi technique decreased the amount of time required to complete a study. The RT Delphi method uses computers to deliver the questions and participants can join at any time over the period of the study. In contrast to traditional Delphi surveys, the participants are not subject to rounds, the responses of the group are available real-time coining the term "round-less". The participants are able to click a button to view the line of reasoning for responses and the displayed responses adjust each time a new participant answers or when a participant changes his or her answer. The "round-less" or RT Delphi has not been validated to results of a traditional Delphi study. (Gordon & Pease, 2006)

Extrapolation

Extrapolation is a quantitative, exploratory technique in which the forecaster uses data from the past to project the future path of a technology. As in exploratory forecasting, extrapolation is based on the belief that advances in technology happen in an orderly and repetitive manner resulting in patterns that can be applied to other technologies (Bright, 1998). The patterns take the form of mathematical S-shaped growth models, exponential growth models (Moore's law), and linear growth models.

overview.

In technology forecasting, s-curves dominate the literature and the two most used s-curves are the Pearl and Gompertz (Martino, 2003). The Pearl[3] is also referred to as the logistic model and is often used to forecast the rate a new technology will replace an existing one (Martino, 2003; Porter et. al, 1991). The Pearl curve integrates the rate of change already achieved and the distance to the upper limit (Martino). The Gompertz[4] curve is commonly used to forecast when a new technology will replace an existing one due to decline instead of innovation (Porter et. al, 1991). The Gompertz curve only includes the distance to the upper limit and this difference between the two curves impacts the accuracy of the forecast (Martino, 2003).

The use of growth curves for extrapolation is based on a few assumptions; the upper limit of the growth curve is known, the correct growth curve is chosen for the data series, and the data describes the coefficients of the growth curve formula correctly (Martino, 1993). The first and crucial step in extrapolation is the selection of the most appropriate model. A study conducted by Young (1993) showed selecting a model that depicts how the historical

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[3] $y = L / 1 + ae^{-bt}$, where L is the upper limit of the growth of variable y, e is the base of natural logarithms, t is time, and a and b are the coefficients obtained by fitting the curve to the data (Martino, 1993)

[4] $y = Le^{-be^{kt}}$, where y is the variable representing performance, L is the upper limit, e is the base of natural logarithms, t is time, and b and k are the coefficients obtained by fitting the curve to the data (Martino, 1993).

data series was created provides better forecasts than selecting a model that best fits the historical data series (Young). After the model is selected the raw data or cumulative data are typically fitted to the curve by linear regression (Martino, 1999; Modis, 2007). The data is then projected, analyzed, and interpreted (Porter et. al, 1991).

Extrapolation is one of the most used forecasting techniques, but most of its development occurred in the 1960s-1970s (Martino, 1993 & 2003). The two areas of development since the 1970s are the use of computers and research on model selection. The use of computers in technology forecasting is a common development for all of the techniques discussed in this paper. According to Martino (2003) the two most notable developments in model selection are Young (1993) and Franses (1994). Young (1993) conducted a competitive study of nine technology growth curves to determine the most appropriate curves for a given data set. Franses (1994) developed a method for choosing between the Pearl and Gompertz curves. The method uses an auxiliary regression equation, $\log(\Delta \log Y_t) = \beta + \gamma t + \tau t^2)$, when τ is significantly different from zero then the data set is logistic in nature (Franses, 1994; Martino, 2003).

advantages and disadvantages.

Forecasts generated through extrapolation are based on logical methods, produce quantitative results, and are reproducible (Vanston, 2003). Extrapolation methods are useful for forecasting when new technologies will emerge in the market (Modis, 2007; Vanston, 2003). These techniques are also useful for determining potential points of change and most appropriate when forecasting a relatively constant environment (Vanston, 2003).

As with many other technology forecasting techniques extrapolation requires an experienced forecaster. Although there have been developments in approaches for selection of appropriate models, this is still a subjective process. The technique also requires reliable historical data, which may not always be available. The upper limit of growth is assumed to be known but in fact it's an estimate (Porter et. al, 1991). If the upper limit is incorrect the forecast will not be accurate (Porter et. al). Perhaps the biggest criticism of extrapolation technique is its lack of ability to account for changes in trends; therefore, extrapolation is not the appropriate forecasting method during a transition in behavior. (Bright J. , 1998; Glenn & Gordon, 2003)

overview.

The assumptions associated with causal models are: the influential components are known, the interactions between components are understood, and the interdependence can be expressed in mathematical terms (Martino, 2003). These assumptions require insight into the fundamental causes of technological change. There are theories of technological change, but these theories are not a reliable basis for generating forecasts; therefore, causal models are rarely used by technology forecasters (Martino, 1999; Martino, 2003; Twiss, 1992).

To develop a causal model the forecaster must first identify the technology being forecasted, the influential elements, the cause-and-effect relationships, and the time period for the forecast (Bright J. , 1998). The forecaster formulates this information into a conceptual model to further understand the interactions and effects (Twiss, 1992). The next step is to depict the conceptual model as a mathematical expression (Twiss). The mathematical expression can be in the form of closed-form analytical models[5] or simulation models[6] (Martino, 1993).

Causal models can be grouped into three types of models; technology-only, technology-economic, and economic-social. Technology-only models assume forecasts can be generated using only elements from within the technology system. Technology-economic models assume economic factors determine technological growth. Economic-social models incorporate economic, social, cultural, and political components into the model (Martino, 1993).

advantages and disadvantages.

As previously mentioned causal models are rarely utilized by technology forecasters. When causal models are employed, it is in the forecasting of adoption or diffusion of innovations (Martino, 2003). Causal models are also useful in determining the impact of altering specific variables within a complex model (Martino, 1999).

The most significant limitation of causal models is the lack of understanding of what causes technological change and how the elements behave within a technology system; therefore models may not accurately represent the technology system (Bright J. , 1998; Martino, 1999). In addition the influential elements and the cause-and-effect relationships are often unknown (Martino, 1999). Lastly, the development of models is extremely costly and time consuming (Bright J. , 1998).

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[5] Closed-form analytical models are expressed as equations or a set of equations where one solution can be expressed analytically in terms of a bounded number of certain known functions (Chow, 1999)

[6] Simulation models are expressed as a set of differential equations but the outcomes cannot be expressed analytically (Martino, 1993).

Tech mining

The term tech mining is short for "text mining of science & technology information resources" (Glenn & Gordon, 2003). Tech mining may be used in many types of technology analyses including: technology monitoring, competitive technological intelligence, technology forecasting, technology roadmapping, technology assessment, technology foresight, technology process management, and science and technology indicators (Porter & Cunningham, 2005). Tech mining is closely linked to literature reviews, environmental scanning, technology monitoring, bibliometrics, and text and data mining. Each of these techniques gathers large amounts of information and searches the information for patterns, key events, and/or to extract textual and/or numerical data. In the tech mining process electronic information is gathered from structured sources (ex. science and technology (S&T) databases) and unstructured sources (ex. the internet) then mining software is used to extract useful information which can take the form of lists, mapped relationships and trend curves (Porter & Cunningham). Tech mining is an exploratory technique that results in both qualitative and quantitative findings.

overview.

Tech mining's origins are literature reviews and technology monitoring (Porter A. , 2009). Prior to the digital age researchers and scientists would search books, newspapers, magazines, etc. to stay informed and learn about developing S&T. Since the digital age this information is collected in S&T databases, patent databases, electronic newspaper abstracts, the internet and various other forms. The tech mining process utilizes these electronic resources and pulls the results into a tech mining software program to look for patterns and trends within the data. The theory behind using tech mining for TF is based on two concepts; 1) technology often follows a development cycle 2) it is possible to recognize indicators of technological advances at various stages of development and use this information to forecast advances in technology. Porter (2009) refers to these indicators as innovation indicators. *Table 4* lists the typical stages of technology development and matches each stage with its key issue and information sources for indicators of change.

Table 4. Information sources for each stage of technology development

Stage of Development	Key Issues	Source
Basic research	Scientific uncertainty	NSF Award; NIH CRISP database; Science Citation Index; MEDLINE; PubMed; Chem Abstracts
Applied research & development	Technological uncertainty	Engineering community; INSPEC; EI Compendex; Trade magazines;
Invention	Technology protection	Derwent World Patent Index; Patent applications; PatStat
Commercial application	Economic uncertainty	Widely available from diverse sources; Trade magazines; New product databases; Business Index; Marketing data sources
Widespread adoption	Social issues	Business and popular press; Lexis Nexis; Factiva: Congressional Record

Note. Adapted from *Forecasting and Management of Technology* (p. 118) by A. Porter, A. Roper, T. Mason, F. Rossini, J. Banks, & B. Wiederhold, 1991, Canada: John Wiley & Sons, Inc. Copyright 1991 by John Wiley & Sons, Inc.; "Innovation Forecasting," by R. Watts & A. Porter, 1997, *Technological Forecasting and Social Change* pp. 29-30. Copyright 1997 by Technological Forecasting and Social Change; and *Tech Mining for Future-Oriented Technology Analyses* (p.6) by A., Porter, 2009, In Futures Research Methods-V3, Chapter 3. Copyright 2009 by The Millennium Project of The American Council for The United Nations University.

In Porter & Cunningham (2005) tech mining steps are separated into three decision phases; intelligence, analysis and design, and choice. In the intelligence phase the forecasting questions are identified, the plan for collecting the data is formed and the data is collected. Porter & Cunningham identify 13 Management of Technology (MOT) issues and concerns where tech mining can be utilized. Although all of the issues are of interest to technology managers, the most important issue for TF is tracking and forecasting emerging or breakthrough technologies (opportunities and threats). To correspond with each MOT issue Porter & Cunningham developed a list of questions and suggested analysis measures for each question to assist in the tech mining process. The questions Porter & Cunnigham developed for tracking and forecasting are listed in *Table 5*. These questions are useful when formualting forecasting questions. For a complete list of MOT issues, questions and recommended measures refer to Porter & Cunningham, 2005, pp. 255-266. After the forecasting questions and plan are established the data is retrieved, reviewed, and refined. In the analysis and design phase the forecaster extracts useful information from the data collected. In this phase basic anaylses are conducted initially and if needed more advanced analyses are employed. When using tech mining for TF, forecasters typically look at trends over time in the form of regression models. The four most common models used are linear, exponential, Gompertz and Fisher-Pry. As previously mentioned tech mining can provide results in several forms: lists, mapped relationships and trend curves. Several examples of the typical tech mining results are illustrated in *Figure 2*. The choice phase is last and is where the forecaster selects from the knowledge gained through the analysis and design phase and decides what information to present in the forecast. In this final stage like most other TF methods, the forecast presents and interprets the forecast results. (Porter & Cunningham, 2005)

Table 5. Tech mining questions for tracking and forecasting emerging or breakthrough technologies

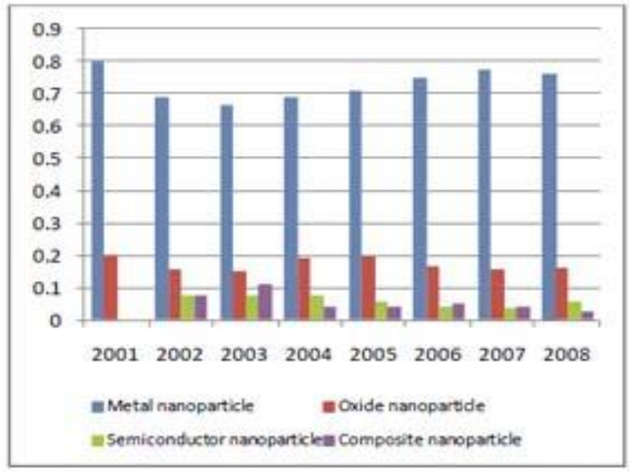
WHAT? (Broad to narrow)
1. What emerging technologies merit our ongoing attention?
2. What facets of this technology development are especially hot?
3. What are new frontiers for this technology (fringes with opportunity)?
4. What are the component technologies that contribute importantly? Significant subtypes of the technology?
5. How does this technological development fit within the technological landscape?
6. What is driving this technology development?
7. What are key competing technologies?
8. How bright are the development prospects for this technology?
9. What are the likely development pathways for this technology?
10. Identify technology fusion potential.
WHO?
1. Who are the available experts?

Note. Adapted from *Tech Mining Exploiting New Technologies for Competitive Advantage* (pps. 255-266) by A. Porter amd S. Cunningham, 2005, Canada: John Wiley & Sons, Inc. Copyright 2005 by John Wiley & Sons, Inc.

List

#	Subject Category	330 China	141 USA
328	Chemistry, Analytical	57%	21%
226	Electrochemistry	40%	12%
126	Nanoscience & Nanotechnology	12%	24%
107	Chemistry, Multidisciplinary	11%	30%
101	Materials Science, Multidisciplinary	6%	23%
74	Biophysics	12%	6%
72	Chemistry, Physical	7%	13%
71	Biotechnology & Applied Microbiology	10%	7%
67	Physics, Applied	4%	17%
50	Biochemistry & Molecular Biology	10%	5%
47	Instruments & Instrumentation	7%	5%
42	Physics, Condensed Matter	3%	9%
40	Biochemical Research Methods	7%	5%

Trend Curve



Mapped relationships

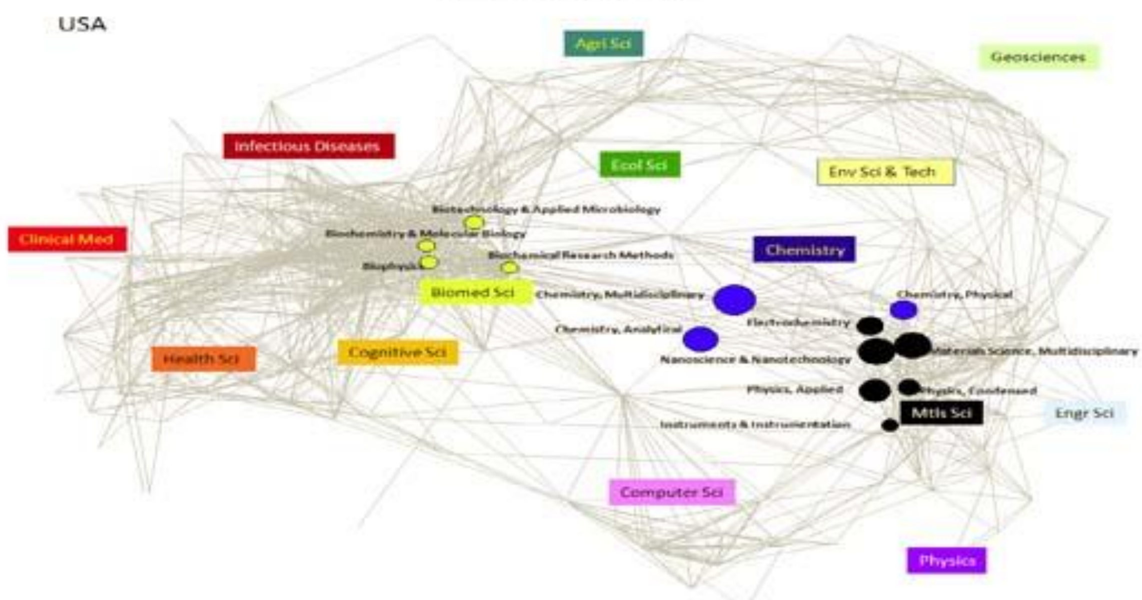


Figure 2: Examples of Tech Mining Results

Note. From "Identifying Emerging Nanoparticle Roles in Biosensors," by L. Huang, A.Porter, and Y. Guo, 2009, *IAMOT 2009-18th, pps-9-11 Retrieved August 1st, 2009 from The Vantage Point* *http://www.thevantagepoint.com/resources/articles/IDENTIFYING%20EMERGING%20NANOPARTICLE%20ROLES%20IN%20BIOSENSORS.pdf* Copyright 2009 by IAMOT.

advantages and disadvantages.

In 2002 the World Future Society surveyed its members to access the value of monitoring and trend evaluation. Wagner (2002) compiled the results of the survey into an article for *Futurist* journal titled, “Top Ten Reasons to Watch Trends”. A summary of the findings are shown in *Table 6*. The survey results highlight some of the advantages of looking for trends, for example: getting early warning signs, gaining an edge on competition, being informed about outside forces affecting your field, being informed about many fields, and being ready for the future. A past criticism of monitoring techniques was that it was labor intensive. Today the computer enables the forecaster to access more information, process more information quickly and uses tech mining software programs to search for patterns within the data. Advances in computers, mining software, and analysis software enable technology forecasters to utilize the vast amount of information available digitally. Another important resource enabled through tech mining is the ability to track emerging technologies which could lead to a better understanding of technology development.

Table 6. Top ten reasons to watch trends

Get investment ideas
Get early warnings
Get confidence
Get an edge on the competition
Get to the heart of a trend
Get goals in balance
Get informed on forces affecting your field
Get informed on forces in many fields
Get a glimpse of emerging futures
Get yourself and others ready for the future

Note. From “Top Ten Reasons to Watch Trends,” by C. Wagner, 2002, *The Futurist,* 36 (2) p.68. Copyright 2002 by The Futurist. Information compiled in table by author

A criticism of tech mining is the quality of the forecast is dependent upon the sources used in the mining process; without the proper data sources crucial elements may not be exposed. Access to the appropriate databases can be expensive; therefore limiting the potential users of tech mining. It is also commonly believed that tech mining requires the use of experts to insure the information is being interpreted correctly and the terminology is fully understood. Tech mining analyses will vary from forecaster to forecaster because most of the relationships found through tech mining are based on co-occurrences. Co-occurrence relationships are based on terms appearing in the same records more often than expected. These types of relationships provide additional information to the forecaster but don’t imply a single future direction.

Roadmaps

"Roadmaps are both forecasts of what is possible or likely to happen, as well as plans that articulate a course of action," (Kappel, 2001, p. 39). A roadmap is a visual representation of the possible future paths of a chosen field of interest and the interactions between the contributing events (Galvin, 1998; Kappel, 2001). They are typically developed by a group of experts in the field of interest, but may be developed using computer software (Kostoff & Schaller, 2001). Roadmaps were first developed by Motorola and Corning in the late 1970s, but it wasn't until 1987 the first journal article was written about the technique (Phaal, Farrukh, & Probert, 2005). Over the past two decades publications about the roadmapping process and roadmapping studies have significantly increased (Coates, 1999; Phaal, Farrukh, & Probert, 2005). Most of the literature describes how roadmaps are used in practice with limited academic research on the fundamental theory of the technique (Phaal & Muller, 2009). Roadmaps were originally developed for strategic planning but the use of roadmaps has spread into research and development, marketing, product development, technology assessment, foresight, and forecasting (Glenn & Gordon, 2003; Kappel, 2001; Kostoff & Schaller, 2001). When used for technology forecasting, roadmaps may be exploratory or normative and can produce quantitative or qualitative results.

overview.

It is important to distinguish between the roadmapping process and the roadmap. The roadmapping process is a "technology planning process to help identify, select, and develop technology alternatives to satisfy a set of product needs" (Garcia & Bray, 1997). A roadmap is the outcome of the roadmapping process where the system is defined and possible future paths are illustrated (Garcia & Bray, 1997). The following section is focused on the development of the roadmap and how it is used for technology forecasting.

Roadmaps are used for many applications, and they are often altered to match the application which results in variations (Phaal, Farrukh, & Probert, 2001). Although roadmaps do not always fit perfectly into categories there are four generic types; science & technology (S&T), industry, product, and product technology (business)[7] (Kappel, 2001). Kappel's graphic depiction of the uses for the four types of roadmaps is shown in *Figure 3.* Purpose of roadmaps. S&T roadmaps outline future developments for a discipline or scientific field with the primary purpose being accurate forecasting (Kappel). Industry roadmaps combine the interests of S&T roadmaps with the industrial landscape (Kappel, 2001). Product-technology and product roadmaps are used for corporate strategic planning. Product-technology roadmaps are concerned with market trends and aligning a company's business plan with perceived trends while product roadmaps are used to demonstrate how a specific product might develop over time (Kappel, 2001). Roadmaps also come in a variety of graphic forms; Phaal, et al. (2001) reviewed over 40 roadmaps and found eight graphic variations including multiple layers, bars, tables, graphs, pictorial, flow charts, single layer, and text. *Figure 4* shows an example of a typical roadmap.

[7] Groenveld (2007) wrote the name product-technology roadmap has been replaced by business roadmap (Groenveld, 2007).

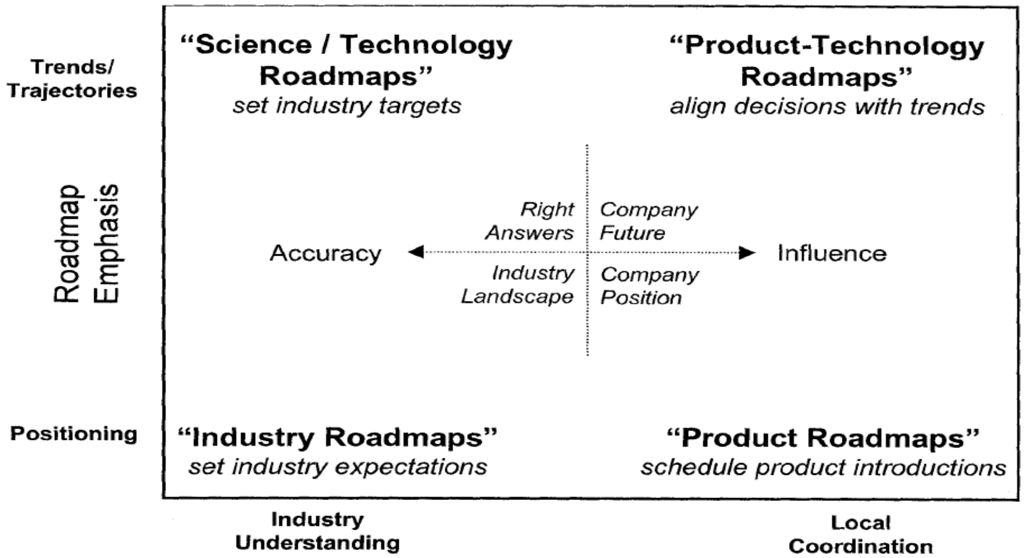


Figure 3. Purpose of roadmaps

Note. From “Perspectives on Roadmaps: How Organizations Talk about the Future,” by T., Kappell, 2001, *The Journal of Product Innovation Management, 18,* p. 40. Copyright 2001 by The Journal of Product Innovation Management.

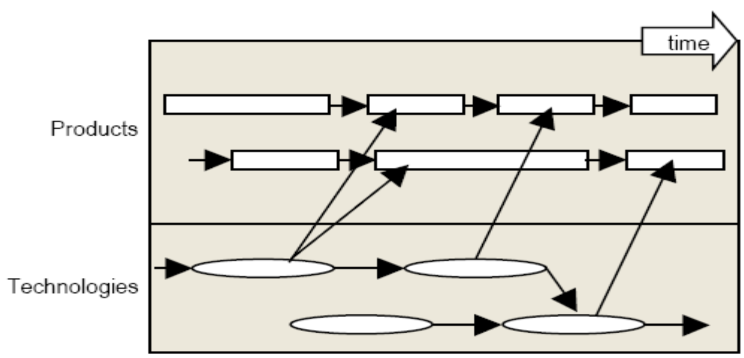


Figure 4. Product roadmap

Note. From “Technology Roadmapping: linking technology resources to business objective,” by R., Phaal., C., Farrukh, D., Probert, 2001, Retrieved November 10, 2008, from Institute for Manufacturing, University of Cambridge: http://www.ifm.eng.cam.ac.uk/ctm/publications/tplan/trm_white_paper.pdf p. 5. Copyright 2001 by University of Cambridge.

Development of a roadmap requires the forecaster to define the focus, scope, and aims of the roadmap (Phaal & Muller, 2009). The conventional roadmap used for technology forecasting is the S&T roadmap (Glenn & Gordon, 2003). According to Kostoff and Schaller (2001) the development of S&T roadmaps consists of four key stages: 1) identifying roadmap nodes, 2) specifying node attributes, 3) connect nodes with links, and 4) specify the link attributes. Nodes are milestones or advancements which may be identified from quantitative or qualitative sources (Glenn & Gordon, 2003). Links are the pathways to connect the nodes and may contain information about time expectations, probability of node occurrence, or degree of impact (Glenn & Gordon, 2003; Kostoff & Schaller, 2001). S&T roadmaps may be used to develop normative or exploratory forecasts, but they are typically used for exploratory forecasting (Kappel, 2001). The two sources of information used for developing roadmaps are experts or computers (Kostoff & Schaller, 2001). Expert based roadmaps are qualitative and the most common type found in literature (Garcia & Bray, 1997; Galvin, 1998; Glenn & Gordon, 2003; Groenveld, 2007; Phaal, Farrukh, & Probert, 2001). Expert-based roadmaps use teams of experts, typically multi-disciplinary, to develop the roadmap through an iterative process (Kostoff & Schaller, 2001). As in the Delphi method, the quality of the roadmap forecast is highly dependent on the group of experts that developed it. The participants identify the nodes and interconnectivity of the system being forecasted. Then they assign either quantitative or qualitative attributes to the linkages (Glenn & Gordon, 2003). Computer-based roadmaps are quantitative roadmaps developed using computer analysis of databases (Kostoff & Schaller, 2001). Roadmaps created using databases employ similar techniques to those used in computer-based environmental scanning to determine nodes and linkages along with quantifying these relationships (Kajikawa, Yoshikawa, Takeda, & Matsushima, 2008; Kostoff & Schaller, 2001). A recent development is the use of computer-based roadmaps to support the expert-based approach (Kajikawa, Yoshikawa, Takeda, & Matsushima, 2008).

advantages and disadvantages.

A roadmap is a communication tool as well as a forecasting technique which allows organizations to gain internal insight as well as forecasting information (Glenn & Gordon, 2003; Phaal & Muller, 2009). They are widely used by industry, academia and government to help develop a consensus among decision makers or a group of experts (Garcia & Bray, 1997). Roadmaps typically employ a range of perspectives which can enhance the forecasting process and results (Porter, 1999). They not only provide a forecast but can be used as a strategic plan for how to arrive at a future target (Garcia & Bray, 1997; Glenn & Gordon, 2003; Kappel, 2001; Kostoff & Schaller, 2001). Roadmaps are viewed as useful tools for aligning the path of a technology with commercial expectations (Phaal, Farrukh, & Probert, 2007).

A key weakness of expert-based roadmaps, like Delphi studies, is the output is highly dependent on the knowledge of the participants (Kostoff & Schaller, 2001). The resulting roadmap is also subjective, which some view as a weakness. Expert-based roadmaps are becoming more challenging because of the large amounts of information available to individuals which makes it difficult for any one person to be aware of all contributing factors and possibilities (Kajikawa, Yoshikawa, Takeda, & Matsushima, 2008). Expert-based roadmaps are particularly challenging when performed outside of a company or organization because the forecaster relies on the willingness of experts, usually employees of companies in the field of interest, to share information which may be viewed as proprietary or as offering a competitive advantage. Like most forecasting methods both expert-based and computer-based roadmaps require large amounts of time and labor (Kajikawa, Yoshikawa, Takeda, & Matsushima, 2008; Kappel, 2001). Finally the roadmapping technique does not have a mechanism to deal with disruptive change (Kappel, 2001).

Theory of Inventive Problem Solving (TRIZ) TF

TRIZ is an invention and engineering problem solving technique accredited to the Russian inventor Genrich Altshuller (Slocum & Lundberg, 2001). Through the review of thousands of patents Altshuller and colleagues developed a theory describing technology evolution along with a set of principles for how to approach problem solving (Terninko, Zusman, & Zlotin, 1998). TRIZ is based on three assumptions:

- *The emergence and implementation of innovation is not random or haphazard (as it might appear), but rather are dictated by certain general evolutionary patterns governing the creation of artificial systems*
- *These patterns can be revealed through study of the history of innovation in various areas, including technology, the arts, social life, etc.*
- *The revealed patterns can be purposefully applied to:*
    - *Predict possible evolutionary "paths," as well as potential dangers associated with these paths.*
    - *Quickly and effectively resolve creative (inventive) problems.*

(Zlotin & Zusman, 2002, p. 19)

The TRIZ problems solving method consists of several tools and concepts which are combined to create innovative solutions. Some of the core concepts include contradiction, resources, ideality, patterns (laws) of evolution, and innovative principles (Rantanen & Domb, 2008; Terninko, Zusman, & Zlotin, 1998). *Table 7* provides a description of each of the core TRIZ concepts. Due to social and political complications, most TRIZ research and development was kept within the Soviet Union until mid to late 1980s (Rantanen & Domb, 2008). In the 1990s when Soviet TRIZ experts began to travel overseas, a surge of interest began in the United States (Rantanen & Domb).

Table 7: Core TRIZ Concepts

TRIZ Concept	Description
Contradiction	Inventive problems contain technical and/or physical contradictions (conflicts); Often problems can be solved by removing a contradiction
Resources	Resources are all the surrounding and contributing parts of the environment of the problem; Resources may be used to resolve contradictions
Ideality	Technological systems are evolving towards an ideal state; An ideal system is one that provides the desired functions without existing
Patterns (laws) of evolution	Repeating patterns of improvement found in the history of innovation and are used to move the system towards ideality
Innovative principles	A collection of principles developed from tens of thousands of good, repeated solutions to inventive problems found in patent literature

Note. From *Systematic Innovation: An Introduction to TRIZ*, by J. Terninko, A. Zusman and B. Zlotin, 1998, Boca Raton: CRC Press LLC. Copyright 1998 by CRC Press LLC and *Simplified TRIZ* by K. Rantanen and E. Domb, 2008, Boca Raton: Auerbach Publications. Copyright by Taylor & Francis Group LLC. Information compiled in table by author

overview.

TRIZ technology forecasting was developed sometime after the mid-1970s (Zlotin & Zusman, 2002). It is a quantitative or qualitative technique that can be used for normative or exploratory forecasting, but often focuses on what modifications should transpire to take the technology to the next stage in the technology evolution cycle (Zlotin & Zusman). The results of a TRIZ forecast are not merely predictions but possibly the invention of the next stage of development (Fey & Riven, 1999; Zlotin & Zusman, 2002). A majority of TRIZ textbooks focus on the theory and application of TRIZ for problem solving while the application of TRIZ for technology forecasting is only a small area of use (Altshuller, 1984; Rantanen & Domb, 2008; Salamatov, 1999; Terninko, Zusman, & Zlotin, 1998). The literature on TRIZ technology forecasting is limited, but a useful source is *The TRIZ Journal*. *The TRIZ Journal* is an online journal for TRIZ practitioners and publishes articles on a range of TRIZ related issues including; TRIZ technology forecasting case studies, how TRIZ can be used to improve technology forecasting, and how to practice TRIZ forecasting (TRIZ Archives, 2008).

After reviewing several case studies and articles on TRIZ forecasting, the following emerged as steps for TRIZ technology forecasting:

1. Analysis of the technological system: study the history of the system
2. Technology maturity mapping: determine the systems position on the life cycle by analyzing s-curves
3. Application of the patterns and lines of evolution: used to forecast how to move the technological system to the next level along the evolutionary cycle
4. Formulation of problem: determine what engineering problems need to be solved
5. Solution of problem: solve problems using the analytical and solution tools of TRIZ

(Fey & Riven, 1999; Gahide, Clapp, & Slocum, 2000; Lovel, Seastrunk, & Clapp, 2006; Zlotin & Zusman, 2002; Slocum & Lundberg, 2001)

The first step in TRIZ technology forecasting is the analysis of the technological system. In the case studies reviewed this was in the form of a historical review of the technological system being forecasted. Forecasters did not provide specific reasons for the historical analysis, but the review provides the forecaster with both the history of the technology and the current state-of-the-art which is useful insight during the application of patterns of evolution and identifying technology gaps.

Next the forecaster maps the maturity of the technology being forecasted. The foundation of technology maturity mapping is Altshuller's discovery that technology followed an evolutionary pattern similar to biological systems as illustrated in *Figure 5* (Altshuller, 1984; Gahide, Clapp, & Slocum, 2000). In order to determine the stage of maturity for a technology, Altshuller developed four descriptive curves which are shown in *Figure 6* (Altshuller, 1984; Lovel, Seastrunk, & Clapp, 2006). The first stage of maturity mapping is an extensive patent search on components within or related to the technological system. Gahide, Clapp, & Slocum (2000) developed a database of all the patents used for their case study. The database could be sorted, filtered, and information coded based on the part or system the patent improved. After the patents are collected they are evaluated based on the descriptive s-curves; number of patents over time, level of inventiveness over time, performance over time, and profitability over time. Profitability and performance data are not always available; therefore, forecasters often determine the maturity without one or both of these descriptors (Slocum & Lundberg, 2001; Gahide, Clapp, & Slocum, 2000; Lovel, Seastrunk, & Clapp, 2006). The data for each of the curves is depicted in graph form and compared to the descriptor curves as shown in *Figure 7*. The combined analysis of available descriptor curves reveals the stage of maturity for the technology. The technology's stage of maturity provides insight into the type of change ahead. (Gibson, Clapp, & Slocum, 1999;

Gahide, Clapp, & Slocum, 2000; Slocum & Lundberg, 2001; Lovel, Seastrunk, & Clapp, 2006)

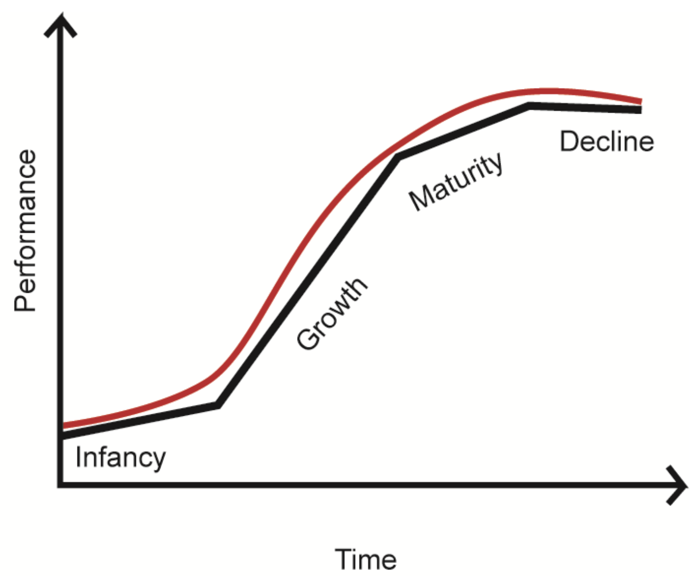


Figure 5: Biological S-Curve

Note. From *Creativity as an Exact Science* (p. 207) by G., Altshuller, 1984, Amsterdam: Gordon and Breach Publishers. Copyright 1984 Gordon and Breach Publishers and "The Application of TRIZ to Technology Forecasting A Case Study: Brassiere Strap Technology," by K. Lovel, C. Seastrunk and T. Clapp, 2006, *The TRIZ Journal*. Retrieved 11 1, 2008, http://www.triz-journal.com/archives/2006/01/09.pdf, p. 6

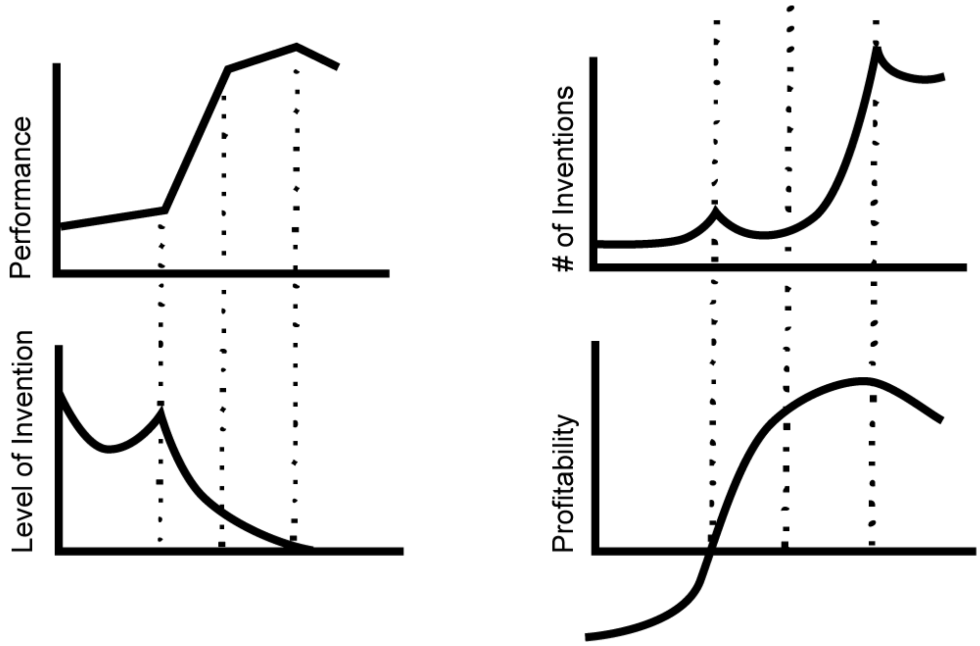


Figure 6: Descriptive s-curves

Note. From *Creativity as an Exact Science* (p. 207) by G., Altshuller, 1984, Amsterdam: Gordon and Breach Publishers. Copyright by1984 Gordon and Breach Publishers and "The Application of TRIZ to Technology Forecasting A Case Study: Brassiere Strap Technology," by K. Lovel, C. Seastrunk and T. Clapp, 2006, *The TRIZ Journal*, January, p. 6. Retrieved 11 1, 2008, http://www.triz-journal.com/archives/2006/01/09.pdf, Copyright 2006 by *The TRIZ Journal*.

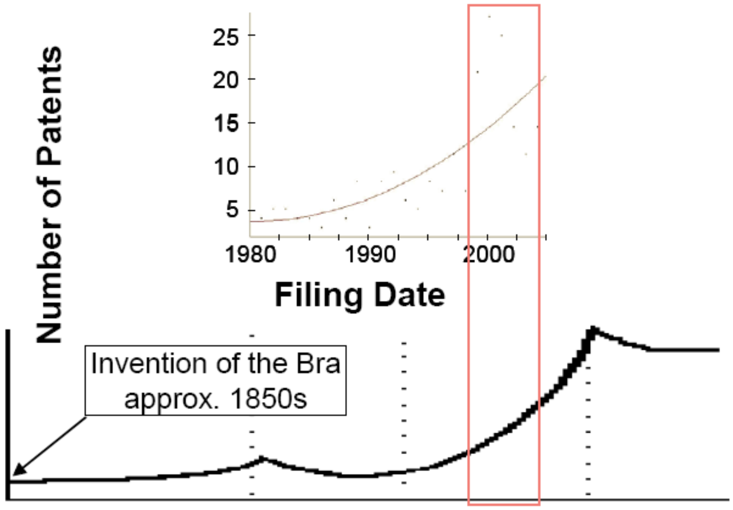


Figure 7: Number of Patents over Time-Fit of Bra Strap Data

Note. From "The Application of TRIZ to Technology Forecasting A Case Study: Brassiere Strap Technology," by K. Lovel, C. Seastrunk and T. Clapp, 2006, *The TRIZ Journal*, January, p. 6. Retrieved 11 1, 2008, http://www.triz-journal.com/archives/2006/01/09.pdf Copyright 2006 by The TRIZ Journal

The next step in TRIZ forecasting is to apply the patterns and laws of evolution. There are eight patterns of evolution as listed in *Table 8:* Patterns of Evolution. The case studies reviewed provided a few examples of how to apply the patterns of evolution, but did not provide much guidance as to the logic behind the selection of one pattern over another or how many should be applied. The most commonly used pattern of evolution employed was evolution towards increased ideality (Gahide, Clapp, & Slocum, 2000; Slocum & Lundberg, 2001; Lovel, Seastrunk, & Clapp, 2006). According to Slocum & Lundberg (2001), application of patterns of evolution results in several possible solution paths and as with all forecasts it is up to the company or forecaster to determine the quality of the forecast and which direction to take. These paths lead into the last two steps of TRIZ forecasting which cross over into new product development because the typical end results are new products. In these last steps an engineering problem is identified from the patterns of evolution that currently has no solution. The forecaster targets this problem or these problems with the help of experts in the area and use TRIZ tools to solve the problem or come up with potential solutions. Often the results are new products or patent ideas. As previously mentioned this crosses over into product development and development of intellectual property which is not within the scope of classical TF.

Table 8: Patterns of Evolution

Evolution in Stages (Technical system follows the biological s-curve)
Evolution Towards Increased Ideality
Non-uniform Development of System Elements (Subsystems evolve at different rates)
Evolution Toward Increased Dynamism and Controllability
Increased Complexity then Simplification (Reduction)
Evolution with Matching and Mismatching Components
Evolution Toward Micro-level and Increased Use of Fields
Evolution Toward Decreased Human Involvement

Note. From *Creativity as an Exact Science* by G. Altshuller, 1984, Amsterdam: Gordon and Breach Publishers. Copyright 1984 by Gordon and Breach Publishers and *TRIZ: The Right Solution at the Right Time* by Y. Salamatov, 1999, The Netherlands: Insytec B.V. Copyright 1999 by Insytec B.V.

advantages and disadvantages.

TRIZ TF predicts possible directions for future development and potentially new technologies and products. Some believe TRIZ forecasts are more accurate because they are quantitative and based on the technology evolution cycle (Fey & Riven, 1999). TRIZ TF also provides insight into the maturity of a technology which can help determine the next level of innovation and detect when old technologies will be replaced by new core technologies (Fey & Riven, 1999). Finally, TRIZ TF offers an objective way to assess and forecast technological systems and is not limited by the knowledge of the forecaster or experts.

One of the disadvantages commonly associated with TRIZ TF process is that is can be complicated and can require a large amounts of time. TRIZ TF is also limited because the forecast doesn't result in specific forecast statements; instead it provides future development directions for technologies. It also doesn't give the forecaster an estimation of when the predictions will occur. The most significant limitation of TRIZ TF is the lack of academic use and evaluation for use in TF. Lastly, there is not much information on how to evaluate or present the results from a TRIZ forecast. (Ideation, Inc., 1999)

Combining Technology Forecasting Methods

In the forecasting literature from the 1960s through the 1990s there were many articles written about combination forecasts. These forecasts are also referred to as composite forecasts and are developed from different data sets, different methods, or both

(Armstrong, 2001). Combination or composite forecasts take several individual forecasts and through a variety of approaches combine the results into a single forecast. Clemen (1989) provides an extensive review of forecasting literature on the subject for the thirty years prior. The literature revealed, what is now accepted by most forecast researchers, that forecasting accuracy can be improved by combination forecasts (Clemen, 1989; Mackay & Metcalfe, 2002).

The field of TF also utilizes combination forecasts but instead of combining forecasting results the TF forecasters develop hybrid forecasting methods. Martino (2003) says the core TF methods are rarely used alone. When surveying the 52 TF methods identified by Porter et al (2004), it is obvious many are combinations methods. TF methods are combined to utilize the strengths of both methods while minimizing the weaknesses (Wang & Lan, 2007). There is limited academic literature describing how TF methods are combined but the examples found used intuitive (judgment) approaches rather than systematic (mathematical) (Glenn & Gordon, 2003; Wang & Lan, 2007). An example of how two TF methods may be combined is illustrated in *Figure 8*.

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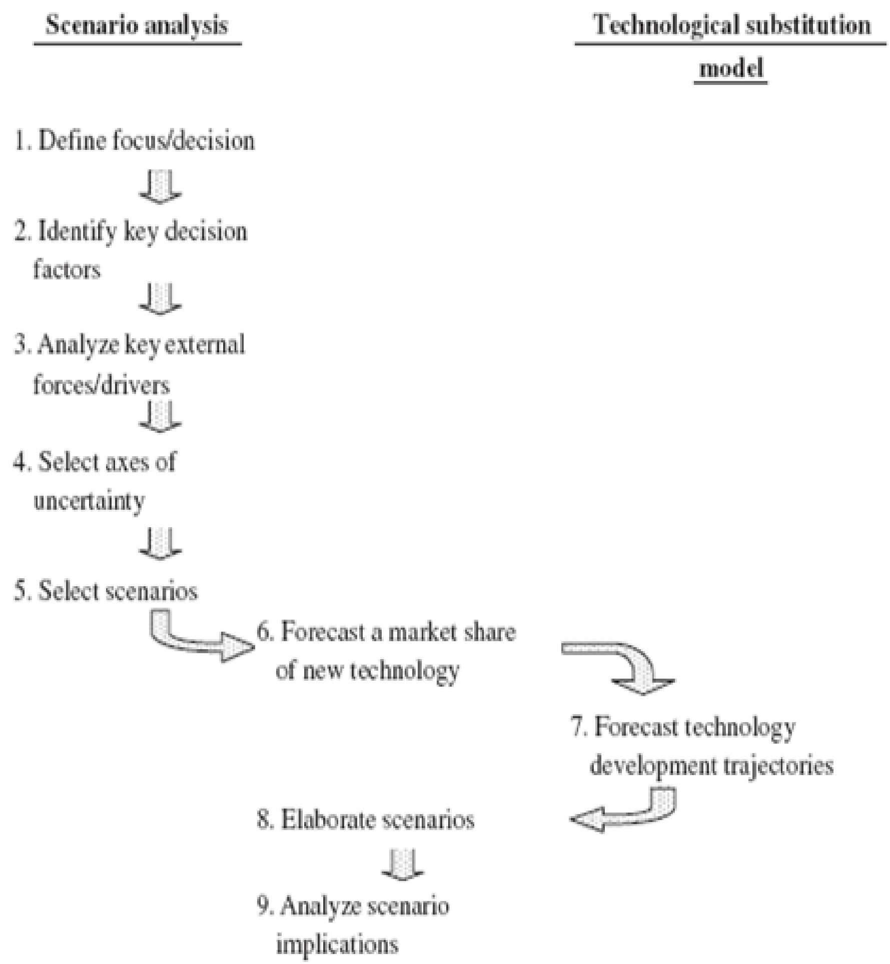

Figure 8. Example of combined TF methods

Note. From "Combined forecast process: Combining scenario analysis with the technological substitution model," by Wang, M. and Lan, W. 2007, *Technological Forecasting and Social Change, 74*, p.361. Copyright 2007 by Technological Forecasting and Social Change.

Air Filtration: Nonwovens

The US air filtration market accounts for over 65% of the filter media made from nonwovens (Pourdeyhimi, 2009). Air filtration is a mature market but it still sees continuous performance improvements and market growth (Galka & Saxena, 2009). Continued concerns about health and safety, energy consumption and sustainability are key drivers for development and innovation in the US air filtration market (Edelman, 2008). In addition the air filter market demands improved performance in lifespan, material use requirements, maintenance costs, strength to improve manufacturability, burst strength for harsh conditions and increases in efficiency and particle size capture (Montefusco, 2005). Nonwoven filter media continue to grow in the air filtration market due to advantages in energy savings, costs, available basis weights, performance and versatility in processes and structures (Pourdeyhimi, 2009).

Filtration Mechanisms and Characteristics

The role of an air filter is to separate unwanted solid particles or droplets from the air stream. The filter must capture and hold large amounts of the unwanted contaminants. The separation is achieved through four mechanisms; 1) inertial impaction 2) direct interception 3) Brownian diffusion 4) electrostatic capture (Pourdeyhimi, 2009). Inertial impaction is a factor when the particles are moving at high to medium velocities and for large (microparticles) particles. When a large particle moves through an air stream it is unable to adjust to changes in the air stream caused by the filter; therefore, the particle continues along the path and collides with the filter media becoming trapped. Direct interception is a factor when the particles in the air stream are a similar size to the pore size of the filter. Due to the size of the particle, it is likely to come in contact with the filter media and become trapped. Brownian diffusion is a factor with nanoparticles. Nanoparticles (fine particle that is measured in nanometers) do not move through the air stream in a straight path, but rather the path is altered by other particles and gases. This irregular path increases the likelihood that the particles will come in contact with the filter media and become trapped. Electrostatic capture is important for all particle sizes moving at low to medium velocities. If particles and the filter media have opposing electric charges, the particles are attracted to the filter media and become trapped within the structure. (Pourdeyhimi)

Characteristics considered when developing filtration media are filtration efficiency, dust holding capacity, filter resistance to air flow (pressure drop), environmental conditions, and energy costs. In air filtration most important performance properties are pressure drop, filtration efficiency and dust holding capacity. The ideal filters have a minimum pressure drop and maximum filtration efficiency. The major physical properties that influence nonwoven media's filtration efficiency are fiber diameter, fiber shape, fiber surface area, fiber density, porosity, filter thickness, pore size distribution and most penetrating particle size. (Pourdeyhimi, 2009)

Types of Nonwoven Media in Air Filters

Nonwoven media for air filtration are made from natural, man-made cellulose and synthetic fibers. Fiber types used in nonwoven media include cotton, wood pulp, polyester, polypropylene, glass, nylon, acrylics, rayon etc. (Montefusco, 2005). The most commonly used are polyester, polypropylene and glass (Pourdeyhimi, 2009). Synthetic fibers are often preferred because of their performance properties; they are more uniform, corrosion resistant, flexible, moldable, electrically and thermally stable, and easily bonded (Pourdeyhimi). Fibers with diameter less than .5 micrometers, nanofibers, continue to be an important area of development for air filtration (Pourdeyhimi).

Web forming technologies for nonwoven air filter media include wet laid, air laid, spunbond, meltblown and composites (Montefusco, 2005). Wet laid nonwovens are very popular due to their efficiency at low basis weights and the uniformity of the fabric. Typical applications for wet laid nonwovens are HEPA filters for clean rooms, HVAC, automotive air intake, and gas turbine and cabin air (Montefusco). Meltblown webs are seeing rapid penetration into many applications because the process achieves a small fiber size, good barrier properties and relatively low costs (Pourdeyhimi, 2009). Spunbond nonwovens have a good dirt holding capacity, but are not as consistent in pore size distribution as wet laid or meltblown webs (Pourdeyhimi). Spunbond webs are often used as a support material for other filtration media. Air laid nonwovens are very popular because the materials are lofty which results in a high dirt holding capacity (Pourdeyhimi). Typical applications for air laid nonwovens are pre-filters, automotives and barrier fabrics (Pourdeyhimi). The most common nonwoven web bonding processes include needle punching, thermal bonding and resin bonding (Montefusco, 2005).

Air Filter Media Classification

Air filters are classified by a Minimum Efficiency Reporting Value (MERV) rating which indicates an expected level of efficiency for a given particle size. This rating is evaluated using the American Society for Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) standard 52.2 test procedure. As shown in *Figure 9* the classification separates the particle size into three groups; 3 to 10 micrometers, 1 to 3 micrometers and .3 to 1 micrometer. Filters with a MERV rating of 13 or higher are used for removal of fine particles in industrial, hospitals/healthcare, and hazardous applications (Pourdeyhimi, 2009).

	ASHRAE 52.2 (Particle Size)			ASHRAE 52.1 (Test)	
MERV	3 to 10 µm	1 to 3 µm	0.3 to 1 µm	Arrestance	Dust spot
1	< 20 %	---	---	< 65 %	<20 %
2	< 20 %	---	---	65-70 %	<20 %
3	< 20 %	---	---	70-75 %	<20 %
4	< 20 %	---	---	> 75 %	<20 %
5	20-35 %	---	---	80-85 %	<20 %
6	35-50 %	---	---	> 90 %	<20 %
7	50-70 %	---	---	> 95 %	20-25 %
8	> 70 %	---	---	> 95 %	25-30 %
9	> 85 %	< 50 %	---	> 95 %	40-45 %
10	> 85 %	50-65 %	---	> 98 %	50-55 %
11	> 85 %	65-80 %	---	> 98 %	60-65 %
12	> 90 %	> 80 %	---	> 98 %	70-75 %
13	> 90 %	> 90 %	< 75 %	> 98 %	80-90 %
14	> 90 %	> 90 %	75-85 %	> 98 %	90-95 %
15	> 90 %	> 90 %	85–95 %	> 98 %	~95 %
16	> 95 %	> 95 %	> 95 %	> 98 %	> 95%
17	> 99%	> 99%	> 99%	> 99%	> 99%

Figure 9. ASHRAE standards

Note. From Nonwovens Product Development Lecture Notes by Pourdeyhimi,B., 2009, *Graduate Course at North Carolina State University* . Raleigh, NC, USA.. Copywright 2009 by North Carolina State University

Conclusions

Technology forecasting is a valuable tool for technology decision-makers to use in the research and development of new technologies and products. There are numerous techniques available, but most were developed over thirty years ago with limited advances to date. Delphi studies and extrapolation are well established techniques while causal models are rarely used due to limitations in understanding the mathematics behind technology evolution. Tech mining expands the traditional literature review by utilizing the vast amount of information available digitally and integrating analytical software to extract useful information. Roadmapping and TRIZ TF are two of the most recent additions to the field of study. Roadmapping is written about extensively while the academic research on TRIZ TF is limited.

Evaluation of TF methods has been primarily summative reviews and assessment of the TF methods is challenging. There is not a standard approach to determining the accuracy and value of a TF forecast. Combination TF forecasts are believed to be superior to single methods but little to no studies have been designed to specifically evaluate the real value of specific combinations. Tech mining is an accessible TF method that currently uses expert opinion techniques to assist in the development of the final forecast. An alternative TF combination forecast that should be explored is the combination of tech mining and TRIZ TF. TRIZ TF may offer additional value to the tech mining forecast by highlighting potential future directions for technologies while the tech mining forecast may provide more insight into the timing of development.

CHAPTER 3: Research Methodology

Purpose of Research

The purpose of this research is to determine if combining tech mining and TRIZ TF forecast results offers improvements over either single method. This research aims to combine two methods not currently used in combination and evaluate the resulting forecasts. The results of the research will provide insight into the value of combining these methods. The following research questions were developed to guide the research process:

RQ1: What methodology should be used for a hybrid technology forecast using tech mining and TRIZ TF?

RQ2: What type of information is obtained from the individual and hybrid TF forecasts?

RQ3: Does the hybrid forecast offer improvements over either single method?

Research Objectives

To answer the research questions the following research objectives were developed:

RO1: To develop a methodology for a hybrid technology forecast through the combination of tech mining and TRIZ TF techniques.

RO2: To identify the type of information obtained from each individual forecasting method and the hybrid TF forecast.

RO3: To assess the hybrid tech mining, TRIZ TF forecast.

a. Determine if the combined forecast offers improvements over either single method.

Research Design

To meet all research objectives the research design is separated into two phases.

Phase I: Develop methodology

RO1: To develop a methodology for a hybrid technology forecast through the combination of tech mining and TRIZ TF techniques.

Phase I began with qualitative research in which the literature on both methods were reviewed and combined to maximize the value of the hybrid method and minimize weaknesses in either method. Tech mining was selected as the base method and elements of TRIZ TF were added to increase the value of the forecast. It was determined from the literature that steps 1 and 2 of TRIZ, steps listed on page 37, may add value when combined with tech mining. TRIZ steps 4 and 5 were intentionally disregarded because these steps are considered outside of the scope of TF. See the Appendix A for the hybrid methodology developed as part of Phase I.

Phase II: Development and evaluation of individual and hybrid forecasts

RO2: To identify the type of information obtained from each individual forecasting method and the hybrid TF forecast.

a. Document tech mining and TRIZ TF processes and results.

To identify the type of information resulting from each method and to determine if the hybrid forecast offers improvements over either single method, forecasts were developed using both tech mining and TRIZ TF and the forecasting processes were documented. The forecasts were conducted for the purpose of guiding research and development direction and the future of air filtration media was used as the forecasting topic. Each forecast was developed using historical data and forecasted for a known period of time. The time period studied was 1950-2000 and a forecast was developed for a 5 year (2005) and mid-term 10 year (2010) time frame. The following forecasting goals and questions were modified from Porter & Cunningham (2005) and used in the development of the technology forecasts.

1. Assess the maturity of current technologies and trends.
2. What current technologies or trends merit ongoing attention?
3. What emerging technologies or trends merit ongoing attention?
4. What are the component technologies that contribute importantly?
5. What is driving this technology development?
6. What are the likely development pathways for this technology?
7. Who are the available experts?

RO3: To assess the combination tech mining, TRIZ TF forecast.

a. Determine if the hybrid forecast results offers improvements over either single method.

The forecasting processes for tech mining and TRIZ TF forecasting methods were documented and the methodologies and forecasts were qualitatively evaluated. The evaluation criterion for the qualitative assessment was developed from the literature review and included ease of use, evaluation of time, comparison of results for type of information provided and accuracy. The list of evaluation criterion is shown in *Table 9*. Each forecast also resulted in a report that included a series of predictions based on the information provided by the forecast method. When possible the predictions were categorized as short term, 5 years, or long term 10 years. The predictions were evaluated for accuracy using a modified version of the classification approach developed by Wise (1976). In this study each prediction was classified as fulfilled, in progress or not proven. An example of the classification approach used in this research is illustrated in *Table 10*. The evaluation approach developed here also includes determining factors for classifying a prediction in one of the described categories. The predictions were placed in the classes based on evidence found in scholarly or industrial literature and patents data at the time the predictions were evaluated.

Table 9. Qualitative evaluation of forecasts

Category	Description
Evaluation of ease of use	Comparison of the complexity of each forecast
Evaluation of time	Comparison of the amount of time to complete each forecast
Value of information	Ability to address forecasting questions
Comparison of accuracy	Forecast statements are made and can be proven or disproven

Table 10: Comparison of accuracy

Classification	Description	Determining factors
Fulfilled	The prediction occurred as predicted	1 or more patents or applications filed describing the prediction; or 1 or more scholarly or industry written sources validating the prediction
In progress	The prediction was visibly evident at the time predictions were evaluated, but had not become solidly or completely established	1 or more patents or applications filed describing the prediction; or 1 or more scholarly or industry written sources indicating the prediction is in progress
Not proven or unable to prove	The prediction had not been fulfilled, or at the time predictions were evaluated was not technological possible	No patent or literature evidence describing the prediction; and/or at the time the predictions were evaluated, no scholarly reviewed papers stating the prediction isn't technological possible

Note. Adapted from *The Accuracy of Technological Forecasts: 1890-1940* by G. Wise, 1976. Futures , 411-419. Copyright 1976 by Futures.

Limitations of study

Although much effort was put into the design of the research methodology, a few limitations have been identified. The most significant limitation is that the study was conducted by one person and represents a single approach to search queries, patent assessments and interpretation of findings. If the technology forecasts were conducted by a researcher with different background and experience, the results may be different. Another limitation of the research is the time period selected for evaluation. A historic period was selected to provide the opportunity for evaluation of accuracy of the forecasts but using a historical period introduces some bias to the study. All resources used in the forecasts were limited to the time period but it is impossible to remove all knowledge held by the researcher for the related events that followed the time period under evaluation. Another limitation of the study that should be noted is the articles, patents and detailed records are in English. Documents that were originally non-English were included if an English detailed record was available. Patents that included a US or English language filing were included in the patent review of level of inventiveness (LOI).

Scope and delimitation of study

This study limited the scope of the research to both a comparison and combination (hybrid forecast) of tech mining and TRIZ technology forecasting (TF) forecasts. There are a myriad of TF methodologies and it was impossible to evaluate all of them. The tech mining methodology was also limited to the use of structured data. The decision to use only structured data was made based on two factors 1) the study used a historical dataset which influenced the quality of unstructured data available 2) the text mining software used in the study was best suited for structured data. A historical dataset was chosen to allow for the evaluation of the forecasts for accuracy which would have otherwise been impossible without revisiting the study 5-10 years after its completion. The historical dataset also influenced the quality and amount of information available from funding sources and business related databases. The study was also limited to the use of one text mining software program, VantagePoint. The focus of the study was to evaluate the methodologies and forecasts rather than a comparison of software programs. The study was also limited to the use of bibliographic databases available through the NC State University library. The databases selected included Web of Science, Engineering Village, Business Source Complete and Derwent Innovation Index. The TRIZ TF portion of the study requires the evaluation of patents for level of inventiveness (LOI). The full sample of patents was 3, 612 and to make this portion of the study feasible a 10% stratified sample was selected and reviewed. A full explanation of the sampling process is described in the patent search section on page 128. The TRIZ TF was also limited in scope by only considering Altshuller's original 8 patterns of evolution. According to some TRIZ practitioners there are over 400 patterns and lines of evolution. It is possible that some of the patterns not considered would be more suitable for the technology topic than the original 8 patterns.

CHAPTER 4: Research Results

Research Objective 1 was completed during the preliminary research, Phase 1, and the hybrid methodology can be found in Appendix A. The remaining research results are divided into three sections. The first two sections address Research Objective 2 by describing in details both tech mining and TRIZ TF methodologies and the resulting forecasts. The third section of the results addresses Research Objective 3 through the comparison and evaluation of tech mining, TRIZ TF and hybrid forecasts.

Tech mining methodology and forecast

The term tech mining is short for "text mining of science & technology information resources" (Glenn & Gordon, 2003). In the tech mining process electronic information is gathered from structured sources (e.g. science and technology (S&T) bibliographic databases) and/or unstructured sources (e.g. the internet) then mining software is used to extract useful information from the data. The tech mining process is separated into three stages: intelligence; analysis and design; and choice. The forecasts are exploratory using historical information to predict what will occur next. Although the technique uses data and regression the resulting forecast statements are typically qualitative. Following is a detailed description of the implementation of each stage and the forecast results.

Intelligence

The intelligence phase is the planning and data collection stage of the forecasting process. In this stage the forecasting questions were formed and the data collection approach was decided and implemented. As discussed in Chapter 3: Methodology, the following modified forecasting goals and questions were used to develop the forecast:

1. Assess the maturity of current technologies and trends.
2. What current technologies or trends merit ongoing attention?
3. What emerging technologies or trends merit ongoing attention?
4. What are the component technologies that contribute importantly?
5. What is driving this technology development?
6. What are the likely development pathways for this technology?
7. Who are the available experts?

data collection plan.

The data collection plan is the development of the data collection approach. It was significantly influenced by three factors: the technology being researched (topic), the bibliographic databases available to the researcher and the text-mining software used to anaylze the dataset. All three factors worked together to impact the literature coverage and the type and level of detail of information collected for analysis. In this study literature coverage meant not only information sources (journals, conferences, magazines, etc.) but it also meant the stage of technology development that the sources represented. In the ideal senario the dataset for analysis would have included information sources from all stages of technology development but this wasn't the case. One additional unexpected factor in the study was the timeframe used. Because a historical forecast was conducted, 1940- 2000, and this time period covered the early portion of the digital age, the amounts of digital information was limited for some stages of technology development.

The technology topic influences the data collection by the amount of information available on the topic and also guides the database selection process. In this study there were no bibliographic databases available with funding agency information (basic ressearch stage) for the topic of air filtration media. Alternative topics related to public health, medical research or more traditional engineering discplines would have allowed for use of funding agency databases like NIH and NSF.

The bibliographic databases available to the researcher, similar to the technology topic, influenced the amout of information available for collection. In addition the features of the databases used impacted the type of data and level of detail available for anaylsis. Bibliographic databases are listing of references to individual articles, technical papers, dissertations, etc.; these individual documents are called records. Each record includes details about the document that are separated into categories called fields (e.g. title, author name, publication date). Each database reports its own set of fields, some fields are standard across databases, and each database may vary in the number of fields the database outputs. Unstructured sources (e.g. internet) don't use predefined fields so it is more challenging to extract useful information; only structured data was used in this study. The databases selected for this study allowed several options for the number of fields for export; citation, abstract and detailed record; the maximum of amount of information allowed for export was selected. Another feature for consideration is the maximum allowed records for export. Depending on the level of access a user has to a database, the number of records that can be downloaded in a single session varies, which can make the collection process more cumbersome. Another important feature is the file format options available for exporting the data. This feature is closely linked to the text-mining software utilized and is discussed in the following section.

The text-mining software selected to analyze the dataset controls both the file format options for the dataset being imported into the software and the type of analysis that can be conducted. The export file formats of the databases used for data collection and the import formats and filters of the text-mining software must be compatable. VantagePoint was the text-mining software selected for use in the study. VantagePoint was selected because it was developed in-part by Dr. Alan Porter, a lead researcher in Technology Management and expert in tech mining. VantagePoint is a text-mining tool used to analyze the text based searches from bibliographic databases. In VantagePoint, similar to other text-mining software, the dataset is imported into the software which uses filters to recognize the defined fields. The import filter converts the raw data into structured fields that can be cleaned, analyzed and reported in a variety of visual representations of the data. This particular software comes with a large selection of import filters for the most commonly used databases and the option to custom develop an import filter within the software. The creation of custom import filters is not for the standard user but more suitable for individuals with programming experience. As previously mentioned the text-mining software used to analyze the dataset also determines the type of analysis that can be performed. VantagePoint provides multiple options for representation of data including lists, mapped relationships and trend curves.

database selection.

The database selection process took into consideration several factors: coverage of the research topic, representing the various stages of technology development and features of the databases. To select databases with the best coverage of the topic a journal ranking website (SCImago Journal & Country Rank) was used to identify leading journals for filtration and separation. After a list of leading journals was compiled, a filtration expert was interviewed to review the list and offer any additional suggestions for sources. Next searches were conducted for each journal on the list in each database. The databases that were selected are listed in *Table 11* along with a brief description of each database and its features. Web of Science® was selected to represent the basic research stage; EVillage more specifically, Compendex and INSPEC[8], were selected to represent the applied research and development stage; Derwent Innovation Index^{SM} was selected to represent the invention stage and Business Source Complete was selected to represent the commercial and widespread application stage. The use of funding agency data for basic research was also explored but there weren't any funding agency databases available for the research topic. Development of custom import filters was explored but ultimately determined to be outside of the scope of the project.

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[8] Compendex and INSPEC will also be referred to as just EVillage the database used to access both Compendex and INSPEC.

Table 11. Database selection

Stage of Development	Source	Database Description	Database Features
Basic research	WOS®	Scholarly literature in the sciences, social sciences, arts, and humanities and examine proceedings of international conferences, symposia, seminars, colloquia, workshops, and conventions	Includes citation fields, Maximum of 400 records download at a time, export as plain text, VP has import filter
Applied research & development	Compendex	Coverage of engineering research taken from over 6,000 scholarly journals, trade magazines, conference proceedings and technical papers	Maximum of 500 records download at a time, Export as plain text, VP has import filter
	Inspec	Scientific literature in electrical engineering, electronics, physics, control engineering, information technology, communications, computers, computing, and manufacturing and production engineering	Maximum of 500 records download at a time, Export as plain text, VP has import filter
Invention	DII℠	International Patents and value-added information, patent citations, overview of inventions in the global marketplace	Includes citation fields, Maximum of 500 records download at a time, Export as plain text
Commercial and widespread application	Business Source Complete & EBSCO AP News	Definitive scholarly business database, more than 1,300 journals in addition to world-wide news from associated press	Limited fields for export, Maximum of 50 records download at a time, Export at generic RIS

search query and data retrieval.

After the sources are identified the search becomes critical. There are a myriad of options when developing a search query. The most widely used search is a simple Boolean phrasing in a range of fields including; author, subject, title, abstract, publisher, source, etc. In addition many databases have developed indexes where subject matter experts and librarians index articles based on controlled vocabulary. In this study a combination of controlled vocabulary and Boolean phrasing were used depending on the database. In

Table 12 the searches are described in detail. Because Web of Science® didn't offer controlled terms a Boolean search was performed which made retrieving pertinent information more challenging. Engineering Village's Compendex and INSPEC databases both use controlled terms but they are based on different indexes; therefore, two separate searches were performed and then combined in the tech mining software. The patent query was more complex. First several known leading companies in air filtration media were searched in Derwent Innovation Index^{SM} to determine how the patents are typically classified. Then these International Patent Classification codes were researched to identify the most suitable IPC code. It was determined the most suitable IPC was B01D-39-00. The breakdown of the classification is as follows: Section B is performing operations: transporting; B01 is physical or chemical processes or apparatus in general; B01D is separation, evaporation, distillation, crystallization, filtration dust precipitation, gas cleaning, absorption or adsorption; B01D-39-00 is filtering material for liquid or gaseous fluids. The patent query used was a combination of controlled term (e.g. IPC) and Boolean search. In addition, after the initial dataset was collected VantagePoint was used to identify the most cited patents and if they weren't included in the dataset, they were added. Business Source Complete offered control terms and after several search iterations and it was determined that a simple Boolean search would provide the best coverage.

Table 12. Search queries for air filtration

Stage of Development	Source	Search query
Basic research	WOS®	1) TS= (air filter*) 2) TS=(air filtration) 3) TS=HEPA AND filter 4) TS=(high efficiency) AND filter 5) TS=nonwoven AND filter Combined and removed duplicates
Applied research & development	Compendex	(controlled term) air filters OR filter media OR filter AND air (subject/title/abstract)
	INSPEC	(controlled term) filters AND air (subject/title/abstract) Combined and removed duplicates
Invention	DII℠	1) IPC=B01D-39-00 + TS=air filter 2) IPC=B01D-39-00 + TS=high efficiency 3) IPC=B01D-39-00 + TS=nonwoven 4) TS=high efficiency air filter Combined and removed duplicates 5) Used VP to identify most cited patents within dataset and included if not already
Commercial application	Business Source Complete	Subject/title/abstract=(air filter*)

import and clean data.

After the data was collected, the next step was to export the data in compatible formats for VantagePoint. This process was cumbersome for some of the databases because of the limited number of records that could be exported in a single session and the process was particularly challenging for Business Source Complete due to the limited file formats available for export. Once the files were imported into VantagePoint the datasets needed to be cleaned. Cleaning involves removing duplicates, removing any irrelevant records and cleaning up lists. Cleaning up lists involved grouping items that are identified as equivalent (e.g. 3M, The 3M Company, 3M Company). VantagePoint has several wizards for cleaning up author names, British to American spelling, affiliations, etc. that can be modified for each scenario. For further details on approaches to cleaning datasets can be found in (Porter & Cunningham, 2005). After looking at the WOS and EVillage authors, there were some similarities so the two datasets were compared to identify any duplication of records. One hundred and thirty-five records were identified as shared between the two databases. The Vantage Point raw summary statistics for all of the databases are located in Appendix B, *Table 35*, *Table 36*, *Table 37*, *Table 38*.

Analysis and design

In the analysis phase the datasets were reviewed to determine what information could be extracted and how best to represent the data. In the literature, tech mining is most often used for technology monitoring and intelligence, so examples describing how to tech mining for forecasting were limited. One additional challenge was the scope of the forecasting topic. After significant inspection into the datasets and sampling different approaches to analyzing the data, it was determined that a deductive research approach would be best suited for air filtration media. To determine which existing and emerging technologies and trends would be reviewed market and technical reports from the year 2000 were referenced (INDA, 2000; Filter Media Consulting, Inc., 2000). The selected forecasting topics are listed in *Table 13*.

Table 13. Topics for tech mining technology forecast

Category	Research topic
Existing technologies	Glass and/or microglass
	Wetlaid
	Spunbond
	Meltblown
	Needlepunch
	Split film or fiber
	Membranes (in relation to air filtration media only)
Existing trends	Use of electrostatic charge or electret filters
	Use of composite structures
	Increase in HEPA filtration activity
Emerging technologies and trends	Introduction of nanofibers/submicron fibers
	Use of microfibers other than glass
	Antimicrobial functionality
	Use of bicomponent fibers
	Interest in self-cleaning filters

Descriptive and basic analyses

The first sets of results are descriptive in nature and provide a high level view of air filtration activities. To begin the annual and cumulative publications of articles and patents were reviewed for the time period of 1907-2000. The raw data can be found in Appendix A,

Table 39. The cumulative data from 1950-2000 is also shown in *Figure 10*. The graph shows the results from all four databases with each representing a different stage of technology development as previously described. Analyzing the cumulative publications from each stage of technology provides the forecaster information regarding the maturity of the technology. The overall trend for all four datasets is an increase in the number of publications over the entire time period. Both basic research (WOS) and applied research (EVillage) on air filtration were active prior to the 1950s, while patenting didn't begin until the early 1970s and business and general public interests didn't appear until the mid-1980s. As a reminder the patent dataset is aimed solely at air filtration media and therefore narrower in scope than the basic, applied and commercial datasets which used a broader search approach to cover the broader area of air filtration. As indicated with the color coordinated arrows, there are specific points in time for each dataset where there is a steeper rate of growth. These points of change may indicate introduction of new topics, technologies, issues, standards, etc. The graph also shows the rate of growth for patents increasing at a faster rate than the basic and applied research since the start of the patent dataset. The patent total growth surpasses both basic and applied research around 1990. Also in 1990 the basic research publications made a sharp increase. According to the graph the volume and pace of publication of business and public information is significantly less than the other stages of development. It's also common to use S-curves to analyze the maturity of technologies and form predictions, so the four datasets were also fitted to S-curves to determine if any additional information could be gained. Since the searches used to obtain the WOS, EVillage and Business Source datasets cover the broad area of air filtration, which is made up of

multiple technologies with multiple S-curves forming the S-curve for field of air filtration, fitting these datasets to S-curves didn't offer additional information. Looking towards the future the last data points for all four datasets indicate a continued increase in publications in these areas with strong growth in basic, applied and invention areas.

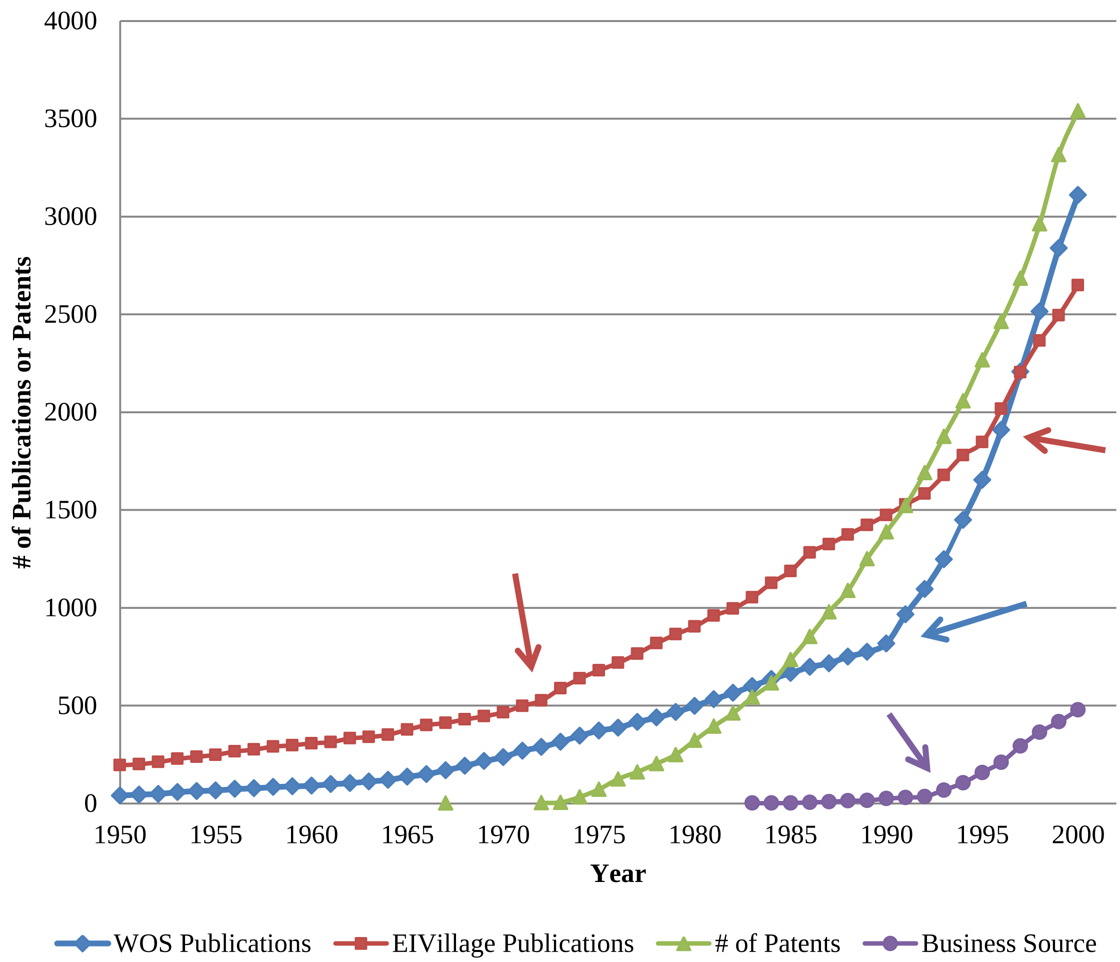

Figure 10. Cumulative air filtration publication data for stages of technology development.

who are the available experts.

One of the first questions in forecasting is answering who are the leaders in a research area. To identify the leaders of basic and applied research for in the field of air filtration the authors that published the most were reviewed for the WOS and EVillage databases. The leading authors were then cross listed with publication years to identify the current leading publishing authors for 1990-2000. As shown in *Table 14* the leading authors for WOS and EVillage are primarily affiliated with academic organizations with the exception of R. C. Brown who works for a government agency. *Table 15* shows the authors' leading subject categories with the largest number of articles falling into Engineering, Environmental Sciences and Public, Environmental & Occupational Health. The table also provides a list of the authors' keywords. Based on the authors' keywords (ex. fiber diameter, filtration media, meltblown, nonwoven, etc) it appears that Liu, B. Y. H, Davis, Wayne T, and Chen, Chih-Cheh are doing research related to fibers and filtration media. There also appears to be several leading authors working on air filtration research related to the medical field. In addition to identifying leading authors for basic and applied research the leading organizations performing research in the area of air filtration were identified. Within the dataset, the organizations were identified by the author affiliation field. The organizations with the highest number of publications were cross listed with the total number of publications over the time period of 1990-2000. As shown in *Table 16* and *Table 17* a majority of the leading organizations are universities but there are three government agencies and one company is included in the lists.

Table 14. WOS and EVillage top 10 authors for 1990-2000

Author Name	Affiliation	Total # of publications	Total #of publications 1990-2000
Liu, B. Y. H	University of Minnesota, USA	45	32
Brown, R C	Health and Safety Laboratory, UK	43	27
Willeke, Klaus	University Cincinnati, USA	24	24
Stenhouse, J I T	Loughborough University,UK	21	15
Deshusses, Marc A	University of California Riverside, USA	19	19
Maenhaut, Willy	Ghent University, Belgium	18	18
Koutrakis, Petros	Harvard School of Public Health, USA	17	16
Smaldone, G C	Stony Brook University, USA	13	13
Davis, Wayne T	University of Tennessee, USA	13	11
Chen, Chih-Cheh	University of Cincinnati, USA	12	12

Table 15. WOS and EVillage top 10 author subject categories and keywords

Author Name	Subject Category	Author Keywords
Liu, B. Y. H	Engineering [23];	particle
	Environmental Sciences & Ecology [12];	equivalent fiber diameter
	Meteorology & Atmospheric Sciences [8];	figure of merit
	Public, Environmental & Occupational Health [6];	mean flow pore
Brown, R C	Engineering [14];	none
	Public, Environmental & Occupational Health [11];	
	Toxicology [10];	
	Environmental Sciences & Ecology [7];	
Willeke, Klaus	Public, Environmental & Occupational Health [16];	respirator
	Environmental Sciences & Ecology [15];	mycobacterium tuberculosis
	Infectious Diseases [4];	microorganism
	Engineering [3];	respiratory protection
		filtering facepiece
		aerosol penetration
Stenhouse, J I T	Engineering [9];	loading
	Meteorology & Atmospheric Sciences [3];	filtration
	Environmental Sciences & Ecology [3];	gas cleaning
	Chemistry [1]	aerosols
		penetration
Deshusses, Marc A	Environmental Sciences & Ecology [8];	biomass control
	Engineering [6];	biotrickling filter
	Biotechnology & Applied Microbiology [4];	waste air treatment
	Meteorology & Atmospheric Sciences [2];	protozoa
Maenhaut, Willy	Meteorology & Atmospheric Sciences [5];	aerosol
	Nuclear Science & Technology [4];	atmosphere
	Chemistry [4];	atmospheric lead
	Environmental Sciences & Ecology [3];	automotive emissions

Table 15 Continued

Author Name	Subject Category	Author Keywords
Koutrakis, Petros	Environmental Sciences & Ecology [9];	air pollution
	Public, Environmental & Occupational Health [5];	acid aerosols
	Engineering [4];	filter pack particle interactions
	Toxicology [3];	bronchoalveolar lavage
Smaldone, G C	Respiratory System [13];	inhaled mass
	General & Internal Medicine [7];	budesonide suspension for
	Public, Environmental & Occupational Health [3]	nebulization
		asthma
		jet nebulizer
		aerosol
Davis, Wayne T	Materials Science [7];	air filter
	Engineering [3];	particle size
	Chemistry [1]	filtration media
		activated carbon
		adsorption
		melt blown fibers;
		nonwoven
Chen, Chih-Cheh	Environmental Sciences & Ecology [9];	electret
	Public, Environmental & Occupational Health [9];	electret filter
	Infectious Diseases [1];	filtering facepieces
	Instruments & Instrumentation [1];	aspiration efficiency

Table 16. Top 10 WOS author affiliations

Organization	Total number of publications	Total number of publications from 1990-2000
University Minnesota	30	27
University Cincinnati	25	25
US EPA	25	23
Caltech	19	18
University Tennessee	19	19
NIOSH	18	18
University N Carolina	17	16
Harvard University	17	13
Suny Stony Brook	14	14
University California Davis	14	13

Table 17. Top 10 EVillage author affiliations

Organization	Total number of publications	Total number of publications from 1990-2000
Health and Safety Laboratory, UK	17	17
University Minnesota	18	14
University California, Davis	14	13
Research Triangle Institute, RTP	11	10
Warsaw University of Technology, PL	11	9
University Cincinnati	9	9
Loughborough University, UK	9	9
University of California, Riverside	9	9
Donaldson Company	11	5
Kanazawa University, JP	9	5

To identify the leaders in invention the DII patent dataset was used. The organizations with the highest number of patents were identified and cross listed for the time period of 1990-2000. As shown in *Table 18* all of the assignees are large companies with the exception of De Ruiter. With the help of the internet a search was conducted and identified Ernest De Ruiter as an individual inventor. After taking a further look at De Ruiter using Vantage Point, it was also discovered that 7 of the patents from 1990-2000 were also assigned to Mann + Hummel GMBH. During the comparison of leading authors for WOS and EVillage several common authors were identified. The complete list of WOS and EVillage authors was also compared to the list of patent inventors to see if any of the inventors were also publishing in basic and applied research sources. The comparison resulted in a list of 53 patents and 105 inventors. The total number of inventors for the dataset was 3239 and only 49% of the 3612 patents records reported inventor names, so only a small percentage of inventors are also publishing through these sources. From the list of common inventors/authors, the top inventor/authors were identified along with the patent assignees and compiled into *Table 19*. As already indicated by the low number of patent inventors also publishing in WOS and EVillage sources, the list of the top inventors/authors further shows there is limited cross over from the basic and applied research into the invention category. After looking further into the inventor/author publishing affiliations, as expected the inventors/authors were employed by the company listed with the largest number of patents. The additional assignee companies listed appear to be collaborators on some of the patents. Although there wasn't a significant cross over between authors and inventors for air filtration, this approach may be useful when researching other fields.

Table 18. Top 10 patent assignees

Assignee	Total number of patents	Total number of patents from 1990-2000
Mitsubishi	96	82
Matsushita Denki Sangyo Kk	116	73
Toyobo Kk	85	72
Freudenberg Group	68	53
Toray Ind Inc	68	47
Nippondenso Co Ltd	59	31
3M	42	30
Daikin Kogyo Kk	36	30
De Ruiter E	30	25
Pall Corp	35	24

Table 19. Top authors and inventors

Inventor & Author	WOS publications	EVillage publications	Patents from 1990-2000	Patent Assignees
Zelikson B M		1	7	Optika Stock Co [7]; Zelikson B M [1]
Ohtsuka K		2	7	Nitta Co Ltd [7]; Fujitsu Ltd [3];
Sakata S		1	6	Takasago Netsugaku Kogyo Kk [6];
Yamamoto K		2	6	Daikin Ind Ltd [5]; Ogane Co Ltd [1]; Tamaru S [1]; Toyota Chuo Kenkyusho Kk [1]
Kinkead D A	1	1	5	Extraction Systems Inc [4]; Integris Inc [1]; Rezuke R W [1]; Kinkead D A [1]; Mykrolis Corp [1]
Pike R D	1		5	Kimberly-Clark Worldwide Inc [5]; Pike R D [1]; Shipp P W [1]

The gain more insight into which countries were leading air filtration research and development, the authors' affiliations by country and the patent priority countries were reviewed and cross listed for the time period of 1990-2000. The results, shown in *Figure 11* and *Figure 12,* for both WOS and EVillage datasets listed the USA as the leading publisher with 39% of all publications in the datasets. This result is certainly influenced by the fact that a majority of the records in the datasets are from English sources. After the USA, the leading countries are Germany, United Kingdom and Japan. The patent priority country results tell a different story as shown in *Figure 13*. The leader in patents granted from 1990-2000 was Japan with 56% of all patents granted. Although Japan isn't shown as a leader in publishing basic and applied research, they are contributing significantly to invention in the area of air filtration media. Japan is followed by the USA with 17% of patents granted and Germany with 11%.

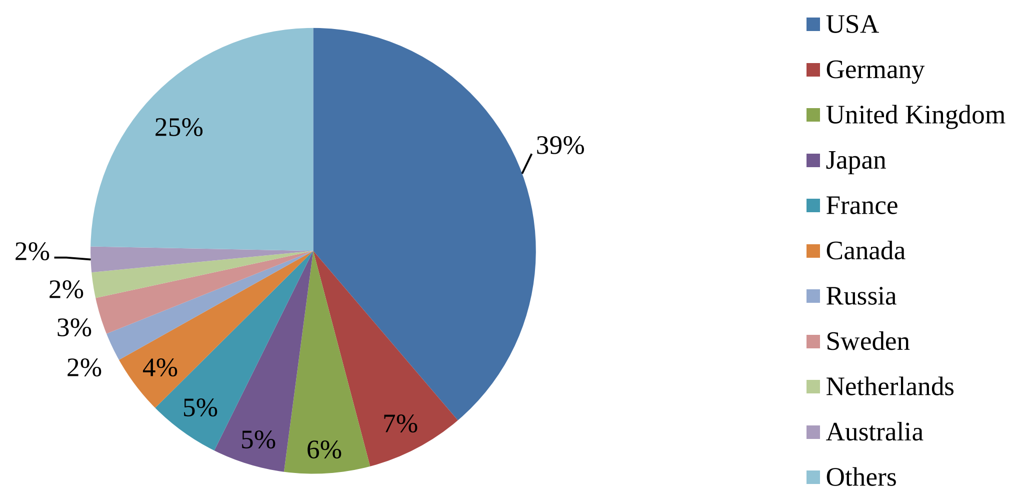

Figure 11. WOS publications by country 1990-2000

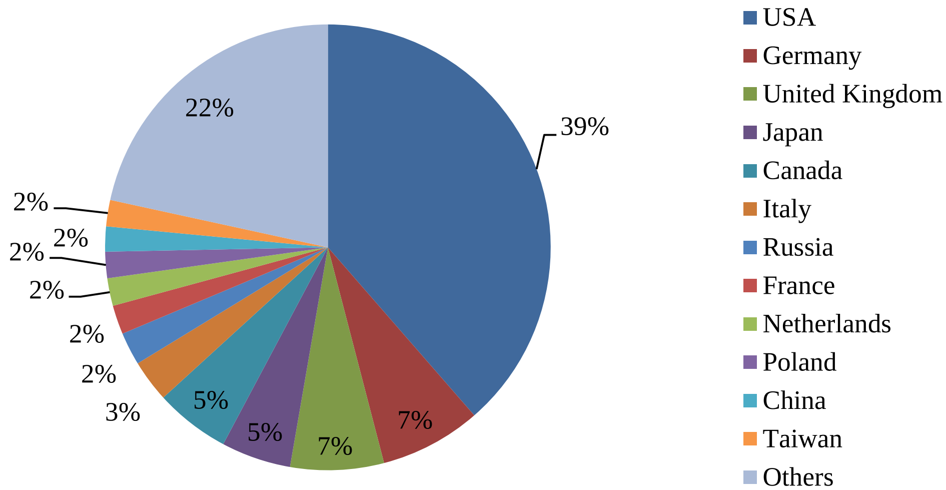

Figure 12. EVillage publications by country 1990-2000

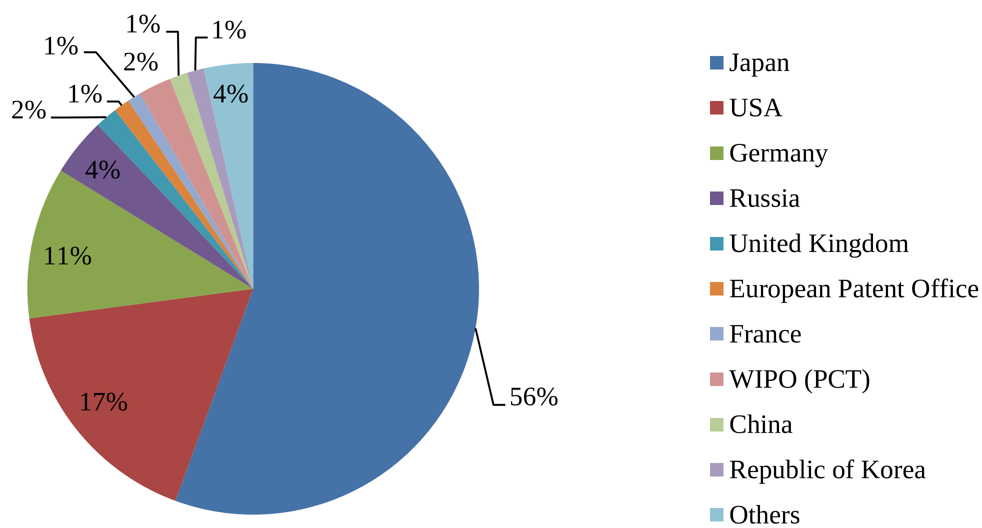

Figure 13. Patents granted by priority country 1990-2000

air filtration media.

Since air filtration media is of particular interest in this study, searches were conducted within the WOS and EVillage datasets to retrieve records that specifically addressed media or nonwoven in the title or abstract. The results of the narrowed search are shown in *Figure 14* and the raw data is listed in Appendix B, *Table 40*. The graph shows the total number of publications on media and nonwoven topics in both WOS and EVillage are lower than the overall air filtration coverage. The media or nonwoven records make up 16% of the WOS dataset and 12% of the EVillage dataset. The low publication records could be interpreted to mean limited basic and applied research was being conducted on air filtration media during this time period. The number of publications is used as an indicator of the maturity of the area and low publications is associated with both early and late stages of development. Since the original air filtration dataset starts as early as 1907, air filtration media would be expected to be in a later stage of development. In *Figure 10* the patent publications for air filtration media starts in the early 1970s and increases at a significant rate so another explanation could be that most of the research and development during this time period was occurring within the industry instead of the academic domain. The typical technology development cycle describes technology progressing along a path from basic research, to applied research, to invention, to commercial and wide spread adoption. In the case of air filtration media there appears to be a lag of basic and applied research behind invention. This could be interpreted to mean basic and applied research were not the sources of innovation during the early stages of air filtration media development but instead the innovation was coming from industry. Also shown in *Figure 14* starting around 1985 both

WOS and EVillage show an increase in publications. After further investigation into the dataset, the WOS period from 1990-2000 covers 93% of all of the media and nonwoven publications. This is a good indicator of increased attention in basic research in this area and that it will continue. The EVillage time period of 1985-2000 accounts for 72% of all of the media and nonwoven publications. This is also an indicator of increased attention in applied research in the area and that it will continue to increase. Based on the publication trends it appears that early air filtration media development was not being published in WOS and EVillage but from 1985 forward publications began to increase and as of 2000 showed signs of continuing to increase. These publication trends also indicate that patent data may be a better source for forecasting for air filtration media as of 2000 but should be reviewed in the future to determine if this has shifted.

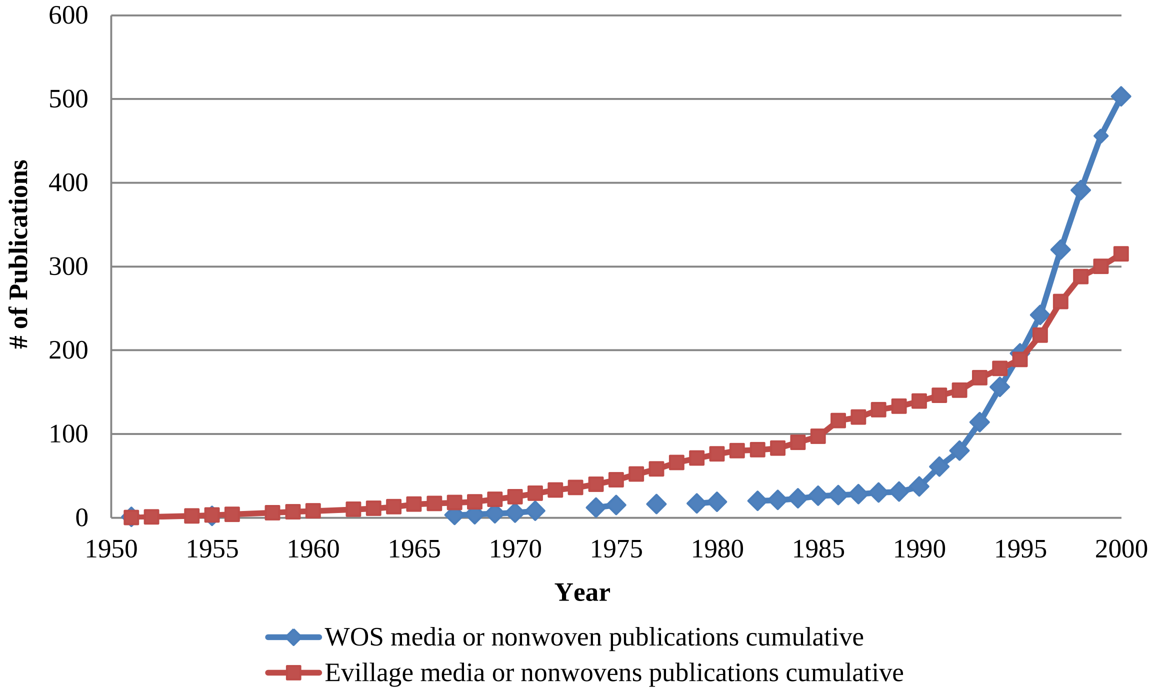

Figure 14. Cumulative media or nonwoven publications

To get a better understanding of the experts in the field of air filtration media the authors of the media and nonwoven subset of WOS and EVillage were reviewed. The summary statistics for the authors are shown in *Table 20* and the table highlights the spread of research across many authors. There also appears to be little collaboration between the authors. The top 10 authors for WOS and EVillage were combined and compiled in *Table 21*. In the top 10 lists there are two authors, Liu, BYH and Davis, WT that were listed in the top 10 authors for air filtration in *Table 14*. Both authors were also thought to be conducting research in fibers and media based on the top author keywords and this was validated through the narrowed dataset.

Table 20. WOS and EVillage summary of authors for media and nonwoven

	WOS	EVillage
Total # of records	503	314
Average # of authors per record	2.6	1.9
Total # of authors	1308	600
Average # records per author	1.2	1.2
% Top 10 authors represent	11.5%	14.6%

Table 21. WOS and EVillage top 10 air filtration media authors

Author Name	Affiliation	Total #of publications
Liu, B. Y. H	University of Minnesota, USA	23
Jaroszczyk, T	Nelson Industries (acquired by Cummins Filtration 1997), USA	9
Ptak, T J	Mark IV Automotive, USA	7
Mlynarek, J	Ecole Polytechnique, FR	6
Davis, W T	University of Tennessee, USA	6
Mukhopadhyay, A	Technology Institute of Textile and Science, IN	5
Nikander, K	University of Helsinki, FI	5
Dietrich, Hans	unknown	5
Schroeder, Edward D	University of California, Davis, USA	5
Wadsworth, L C	University of Tennessee, USA	5

Advanced analyses

One of the strengths of tech mining and using text mining software is the ability to dig into the data and track items over time. Because of these strengths the approach to forecasting was to look into the datasets to establish the maturity, strongest growing and likely pathways for the existing and emerging technologies and trends. The question was how to identify the individual technologies within the datasets. After extensive review of all the datasets, the best approach was to use keyword searches within the record abstracts. EVillage and DII had 98-99% coverage in the abstract field while WOS had 67% of the abstracts for all of the records. Due to the limited coverage of the topic and quality of the information in Business Source Complete this dataset was not included. In Vantage Point there is a find tool that can be used on any field that allows the researcher to look into the field in more detail. This function was used to search through all the abstracts and identify those that included specific keywords and group these into a technology or trend group. These searches were done for the WOS, EVillage and DII datasets for each existing and emerging technologies and trends. As shown in *Figure 15* the find tool allows the researcher to control the search using whole word matching and regular expression searches as well as the addition of operators which include adjacent, and not, or not, near 2, etc. To develop adequate keyword searches requires the forecaster to have strong knowledge of the subject matter or the assistance of a subject expert.

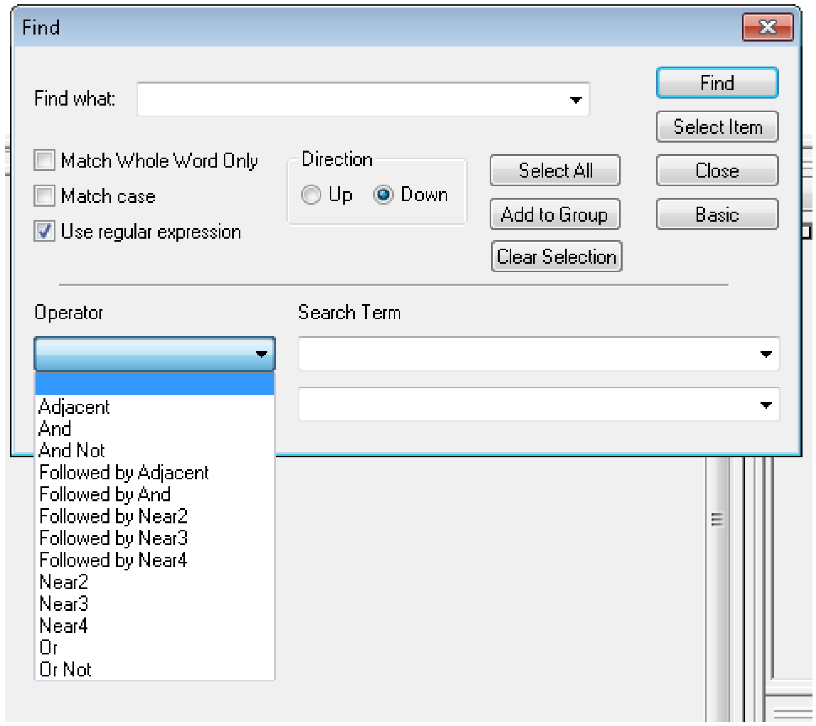

Figure 15. Find function screen shot from Vantage Point

Once the technology and trend groups were formed for each dataset, they were analyzed. Each of the technologies and trends were reviewed by annual publications, cumulative publications, fitting a linear growth model and fitting the Gompertz growth model. The Gompertz is a non-linear regression model often used in tech mining to access maturity and forecast future growth (Porter & Cunningham, 2005). From this analyses, it was determined the best representation of the datasets were the cumulative publications for all three database results and the Gompertz s-curves for the patents datasets. Only the s-curves for the patent datasets were used because of the small number of data points in both WOS and EVillage for most of the technologies and, as previously discussed, a majority of the development during the time period reviewed was being documented through patents instead of basic and applied research databases. The Gompertz model generates a limit which is the upper bound to growth but also allows the forecaster to define this limit. In this study the dataset is patent publications over time which have no actual limits but when necessary forecasters often use reasonable limits to illustrate different forecasting paths (Porter & Cunningham, 2005). Several of the technology and trend datasets had Gompertz models with high limits, so a reasonable limit was also modeled to offer an alternative forecast. The s-curve plots include the cumulative data, Gompertz fit, forecast and upper and lower confidence limits.

Existing technologies results

glass fibers.

Patents that reference glass fibers, as shown in *Figure 16*, have had strong growth since approximately 1975. WOS and EVillage show fewer records that include glass fibers but both have an increasing number of publications on the topic. WOS appears to be increasing publications at a faster rate than EVillage. Using Vantage Point to take a look at the abstracts of the most cited publications within WOS shows that the records commonly referenced glass fiber filters as a standard against other filters, a filter used in a test standard or improvements to glass fiber filter performance. One additional finding was a paper cited 19 times on the topic of chronic inhalation of fiber glass and amosite asbestos in hamsters. This may be a topic to be aware of moving forward. Based on the cumulative patents and publications glass fibers appear to be of continued importance for air filtration media. Taking a look at the s-curve fit and forecast for glass fibers in *Figure 17*, shows the technology on the growth portion of the curve and continuing on this portion of the curve through 2005 and 2010. The full JMP report is shown in Appendix B, *Table 41*. The actual limit of glass fiber patents is not known so the fit is an estimation of what the future may look like for patents related to glass fibers, but the Gompertz model has a good fit with an R-square value of .99 and a limit of 644.

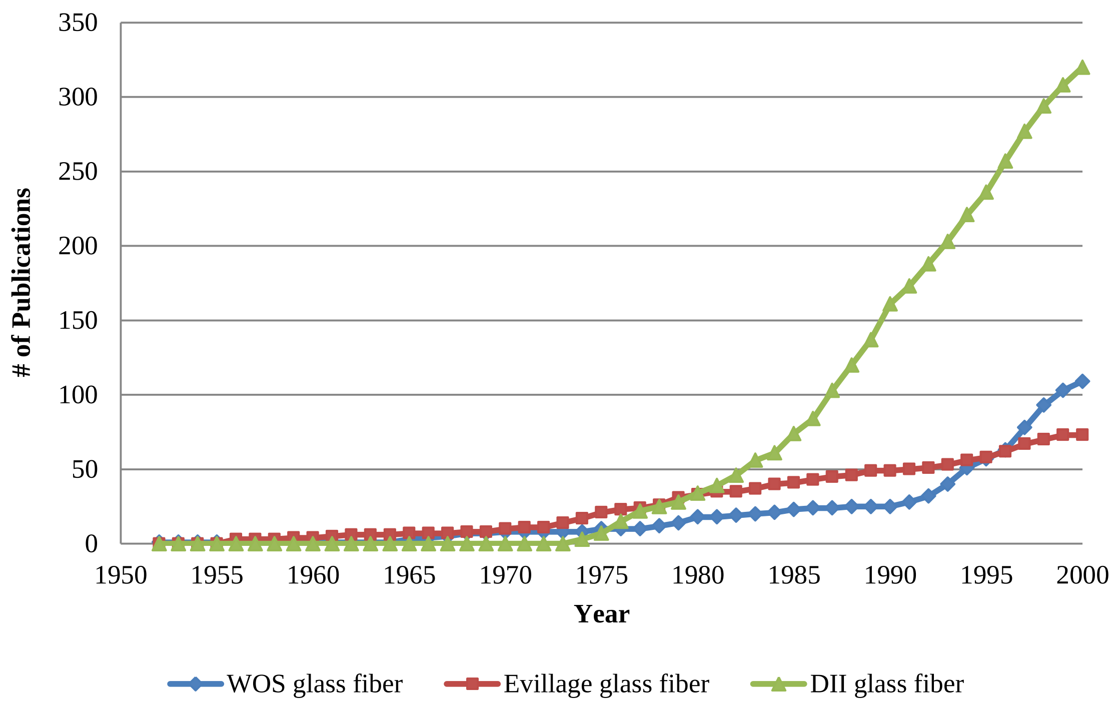

Figure 16. Cumulative glass fiber publications and patents

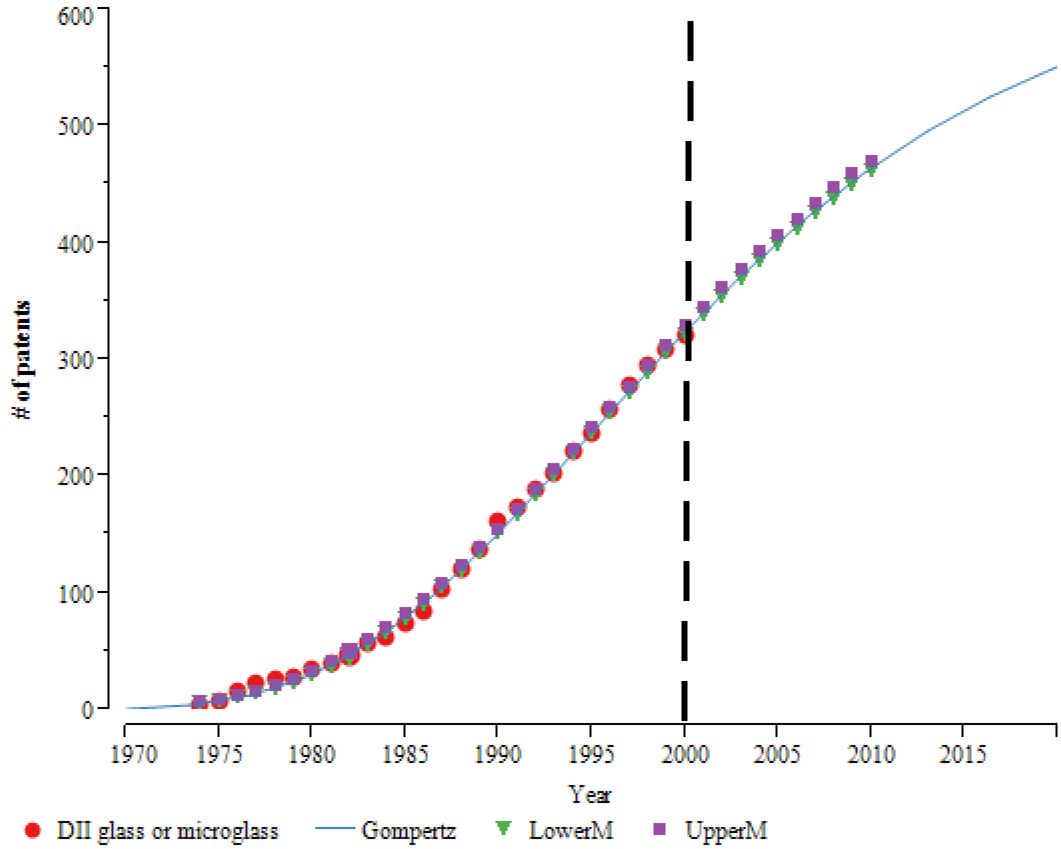

Figure 17. Gompertz model fit for DII glass fiber data

wetlaid.

The results of the patents and publications referencing wetlaid technology are shown in *Figure 18*. The graph shows there has been and continues to be very little basic research, applied research or patents related to wetlaid web formation for air filtration media. It is known that a primary method for forming glass fiber media is using wetlaid processing, but it appears very little invention has occurred related to the wetlaid technology so these two areas are related. Taking a look at the s-curve in *Figure 19* shows a good fit with an R-square value of .96. The full JMP report is shown in Appendix B, *Table 42*. Again here the actual limit of patents related to wetlaid technology and air filtration media is unknown but the model predicts a limit of 10 and wetlaid is predicted to enter into the maturity stage starting around 2015. There is very little patent data available, so it's difficult to predict the future for wetlaid development in air filtration. Due to wetlaid technology's use for making glass fiber media it appears this technology will continue to grow, but the focus on further development of the wetlaid technology is very limited moving forward.

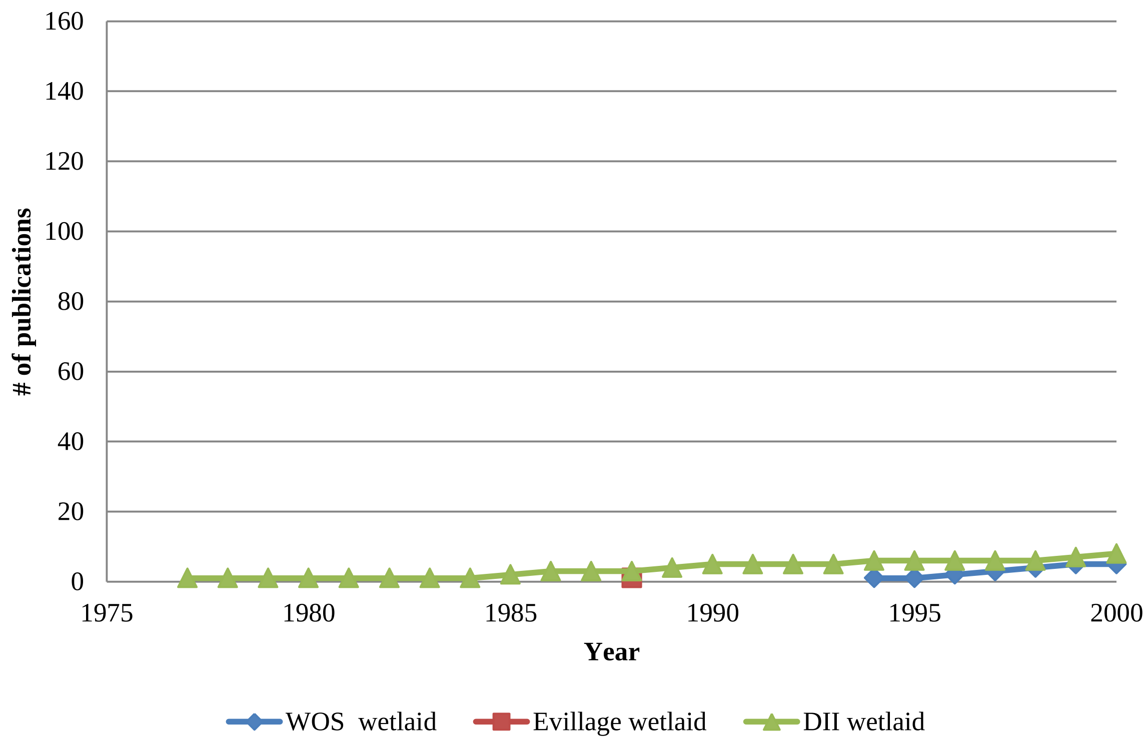

Figure 18. Cumulative wetlaid publications and patents

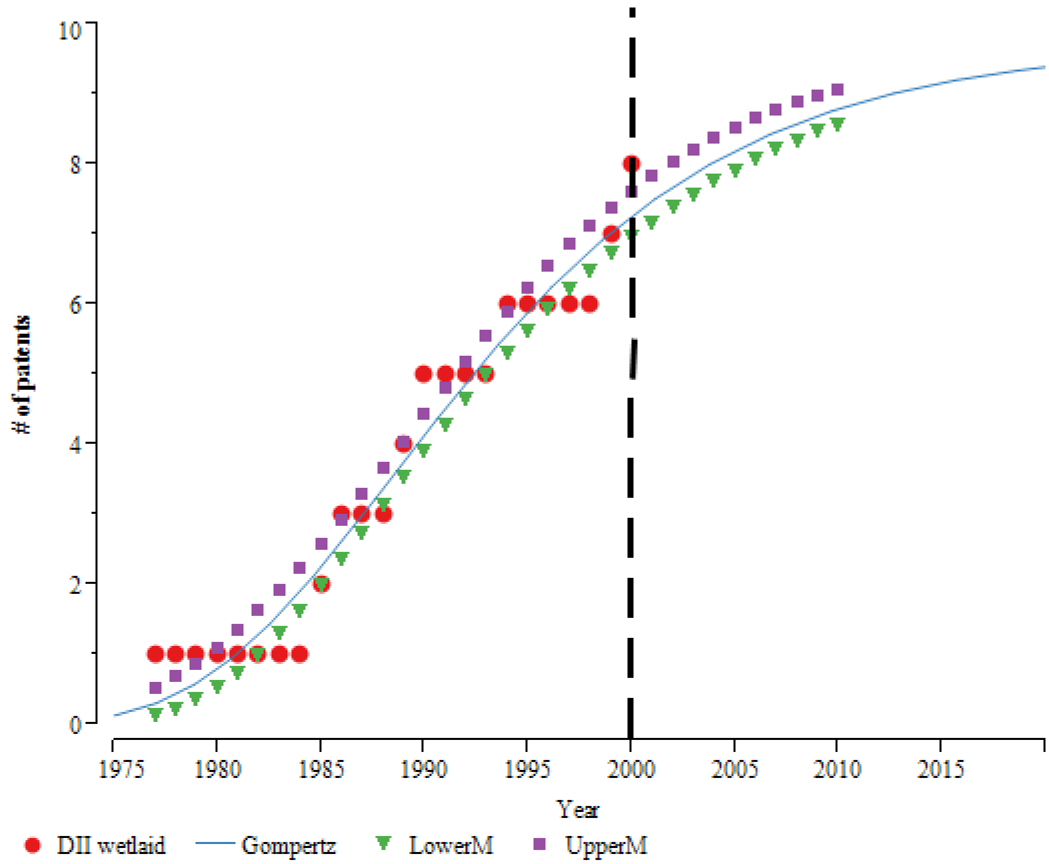

Figure 19. Gompertz model fit for DII wetlaid data

spunbond.

The publications and patent data that reference spunbond web formation technology are shown in *Figure 20*. The graph shows there is little to no basic or applied research publications related to spunbond web formation technology. The graph also shows the air filtration media patents that reference spunbond technology have increased since 1980 with a sharper increase in rate of patenting around 1996. Based on the cumulative data there appears to be very little development on spunbond technology related to air filtration at the basic and applied level but an increasing number of patents referenced spunbond technology from 1996 forward. The s-curve fit for the DII dataset is shown in *Figure 21*. The model reported a good fit with an R-square value of .98 but the limit reported seemed unrealistic at 18, 311, so a limit of 400 was put on the model and both results and confidence limits were plotted in the graph. Changing the Gompertz model limit provides an alternative forecast for the technology, but as shown in the graph doesn't impact the short- and mid-term forecast as much as the long term forecast. The full JMP report is shown in Appendix B, *Table 43*. In the short- to mid-term, from 2000-2010, the differences between the unlimited and limited models doesn't appear to have a large impact on the forecasts. It would be very difficult to predict beyond 2010 due to the significant difference in model limits. Based on the graph spunbond appears to be in entering early growth stage in relation to air filtration but with the small amount of data it's difficult to predict how much growth there will be in this area.

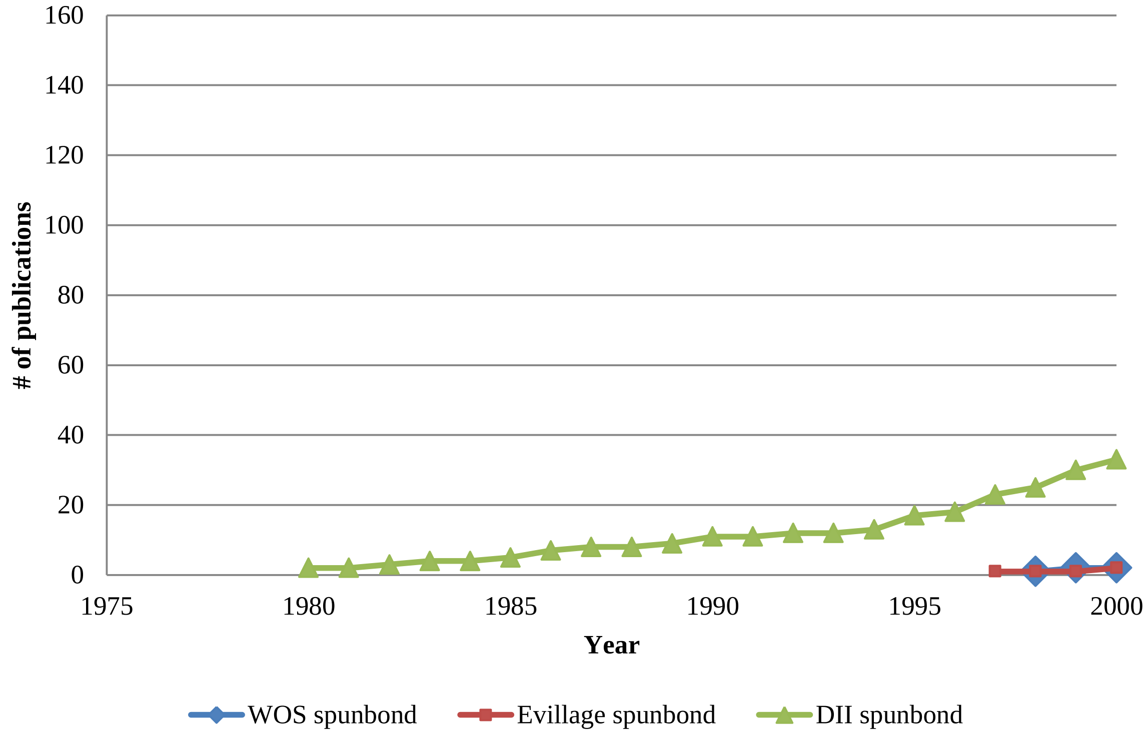

Figure 20. Cumulative spunbond publications and patents

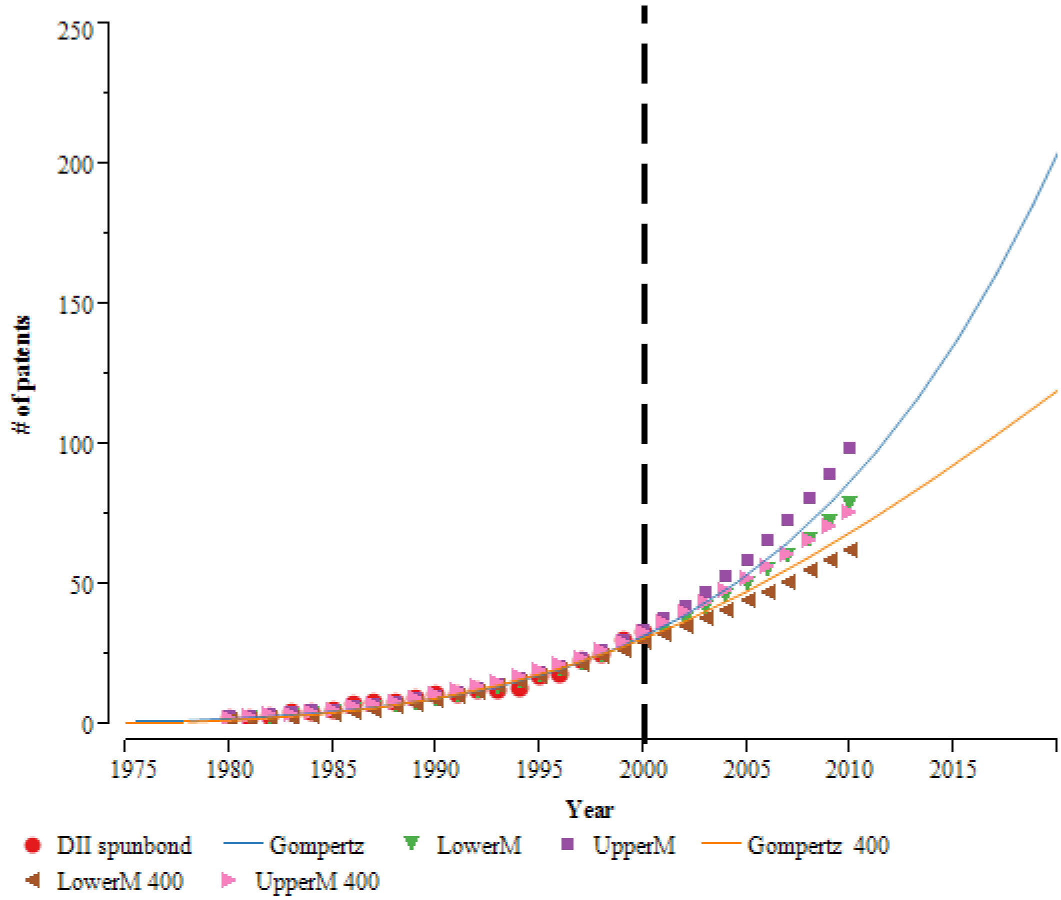

Figure 21. Gompertz model fit for DII spunbond data

meltblowing.

The meltblowing related publications and patent data is shown in *Figure 22*. The graph shows a similar low number of basic and applied research publications as did glass fibers, wetlaid and spunbond technologies. The patent data differs from the basic and applied researcg by showing a continual increase in the number of patents that reference meltblow technology. The rate of patents granted increased sharply around 1992 and have continued to increase at this rate. Based on the cumulative data the increase in patents related to meltblow technology should continue to increase after 2000. Taking a look at the s-curve fit and forecast for meltblowing technology in *Figure 23*, shows the technology on the growth portion of the curve and continuing on this portion of the curve through 2005 and 2010. The s-curve has a good fit with an R-square value of .98. The full JMP report is shown in Appendix B, *Table 44*. The actual limit of meltblowing technology related patents is not known but the model reported a limit of 260.

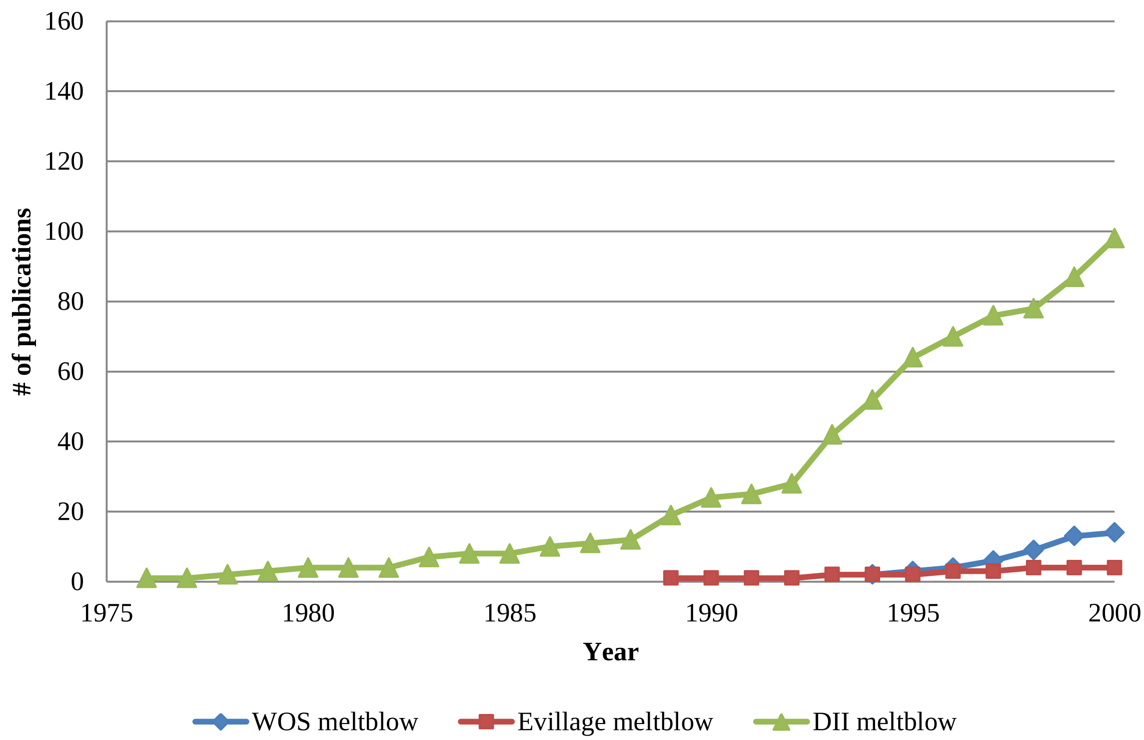

Figure 22. Cumulative meltblowing publications and patents

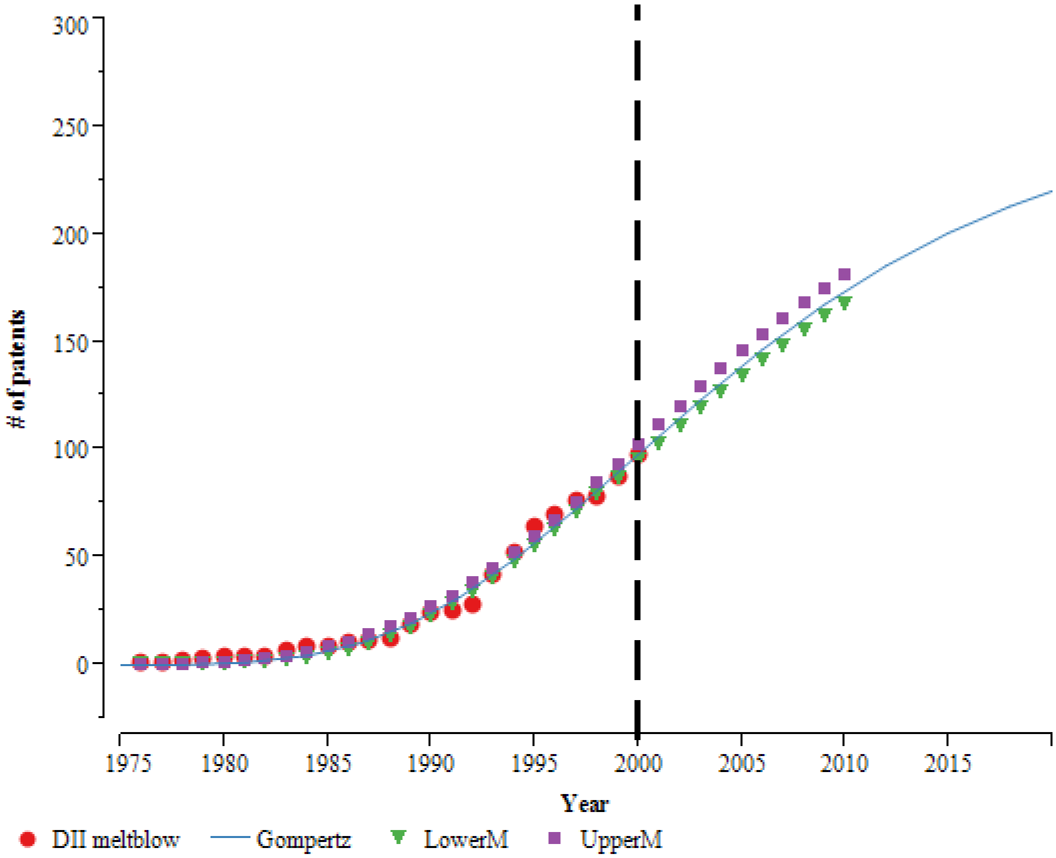

Figure 23. Gompertz model fit for DII meltblowing data

needle-punch.

The cumulative data for publications and patents related to needle-punch technology follows a similar trend to the previous technologies reviewed. There are limited basic and applied research publications but a continued increase in patents granted since 1975 as shown in *Figure 24*. From 1980-1995, there were approximately 40 patents granted every 5 years, but this rate decreased slightly from 1995-2000. The s-curve data in *Figure 25* has a good fit with an R-square of .99 and shows needle-punch technology for air filtration in the growth stage. The full JMP report is shown in Appendix B, *Table 45*. The actual limit of patents related to needle-punch technology is unknown but the model reported a limit of 173. Using the s-curve to forecast for 2005 and 2010, the trend indicates continued growth but the rate appears to slow down around 2015.

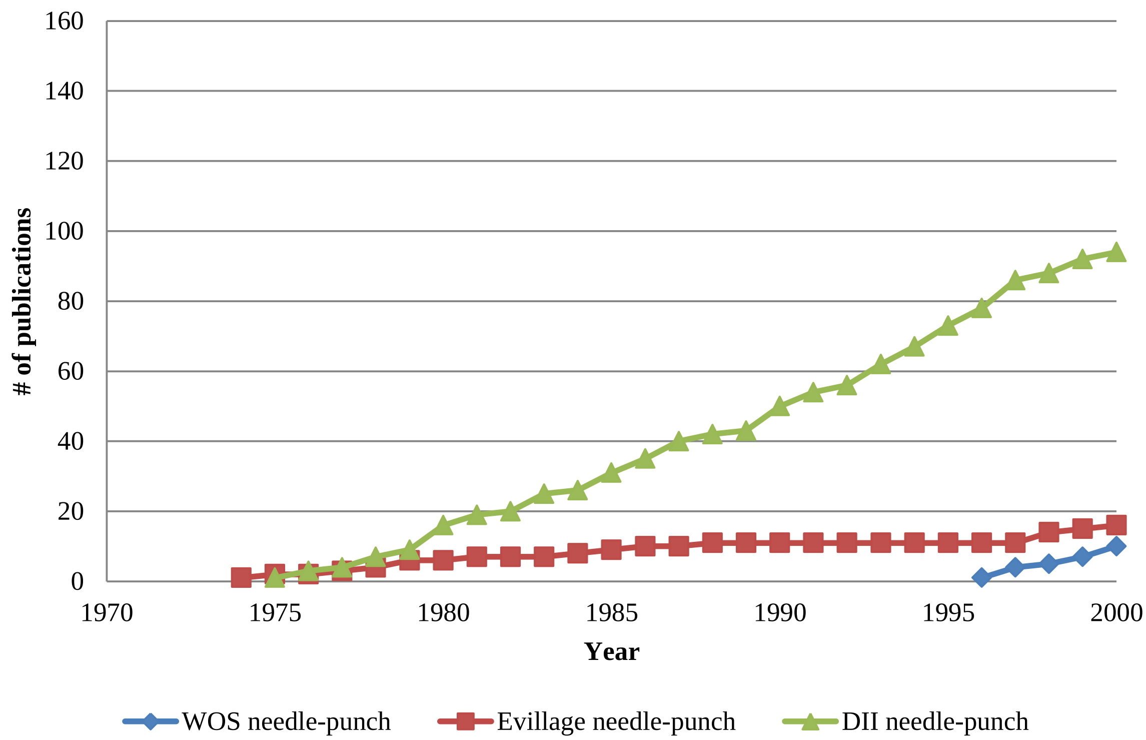

Figure 24. Cumulative needle-punch publications and patents

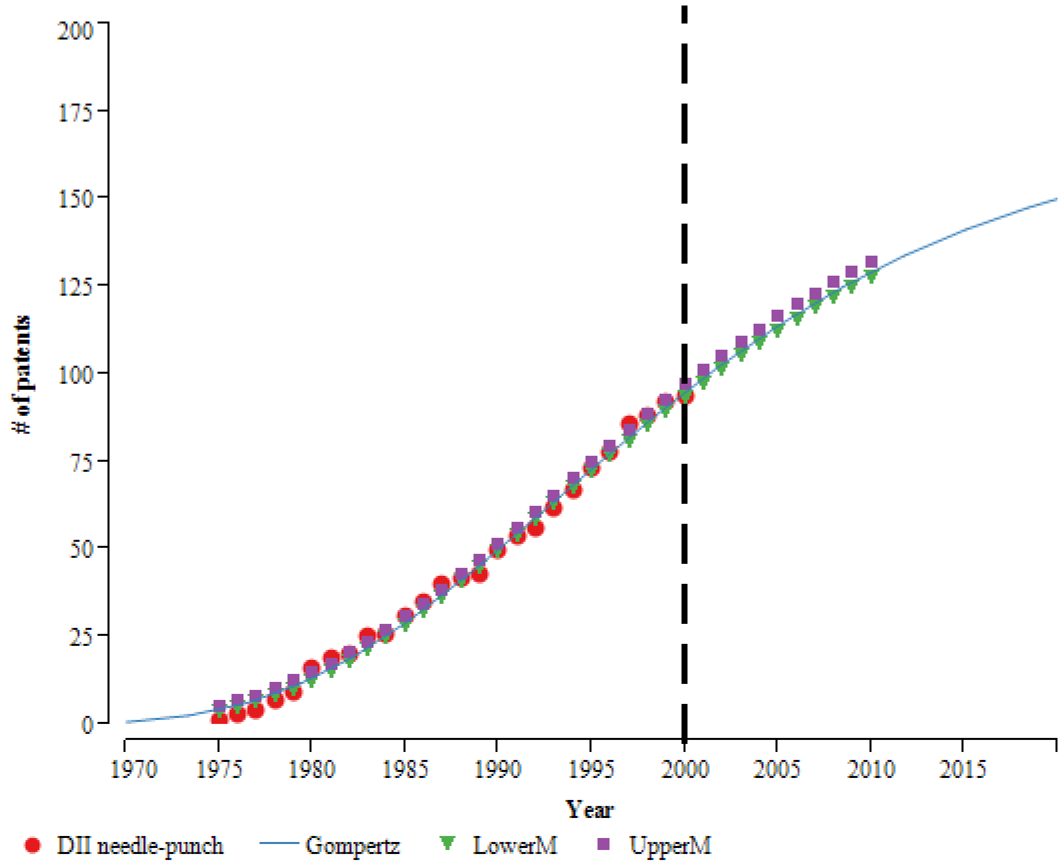

Figure 25. Gompertz model fit for DII needle-punch data

split film or fibers.

At first glance the split fiber/film technology related cumulative data, shown in *Figure 26*, looks similar to the wetlaid data. There is limited to no basic and applied research publications and a small number of total patents in the area. Using Vantage Point to review the dataset, a relationship was observed between split fiber/film records and records that referred to electrostatics in the abstract. 13 out of the 19 split fiber/film records were also in the electrostatics group. The results for the use of electrostatics are discussed later. It appears that one use of splitting fibers/film in the formation of nonwoven webs is in the formation of electret filters, so split fiber/film technology is actually a technology used to create charged media. Electret filter is a term often used to describe filtration media that has been electrostatically charged and they are also referred to as charged media. The remaining 6 records were also reviewed and these referenced splitting for two purposes, the first was splitting yarns for use in air filters and the second was a nonwoven process for making fine fibers using hydroentangling to split the fibers. The cumulative data for patents in the area doesn't show a significant rate of change. The s-curve result, shown in *Figure 27*, has a good fit with an R-square value of .97 and shows the technology in early portion of the growth stage. The full JMP report is shown in Appendix B, *Table 46*. Again, the actual limit of patents related to split fiber/film for air filtration media is unknown but the model reports a limit of 49. According to the s-curve and forecast this area is predicted to increase for 2005 and 2010 but since dataset is small so it's difficult to confidently predict the future values. Moving forward the split fiber/film technology should be divided into subcategories to observe differences in technology and applications.

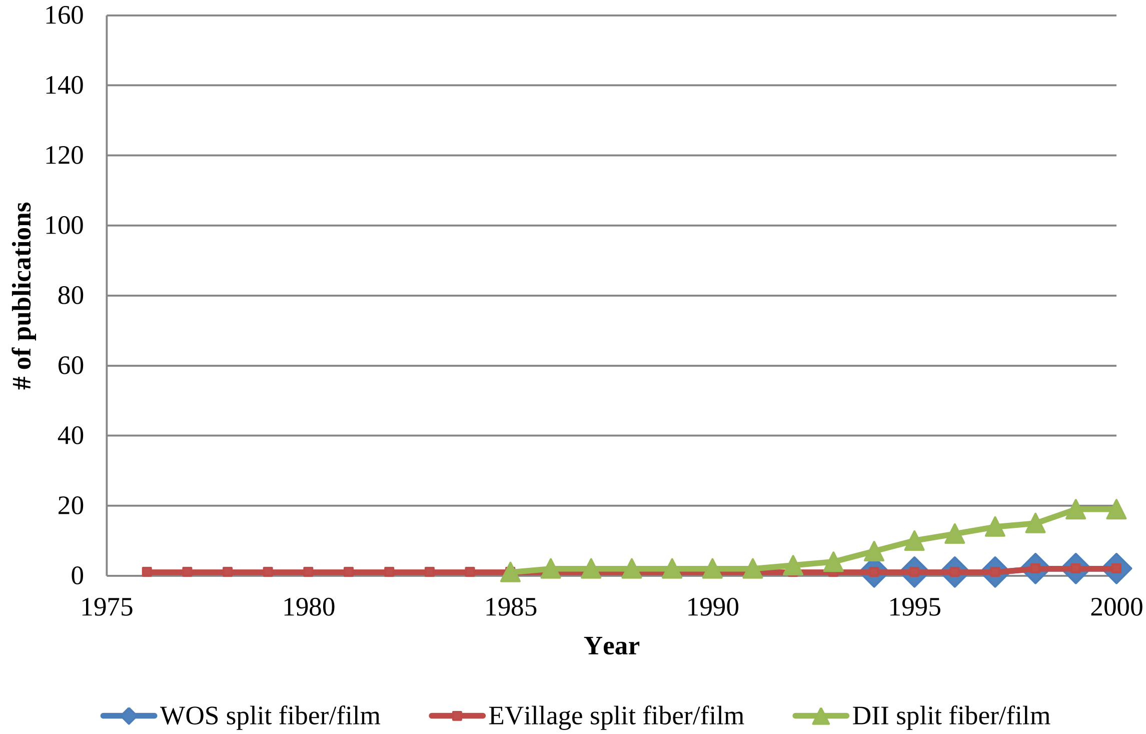

Figure 26. Cumulative split fiber/film publications and patents

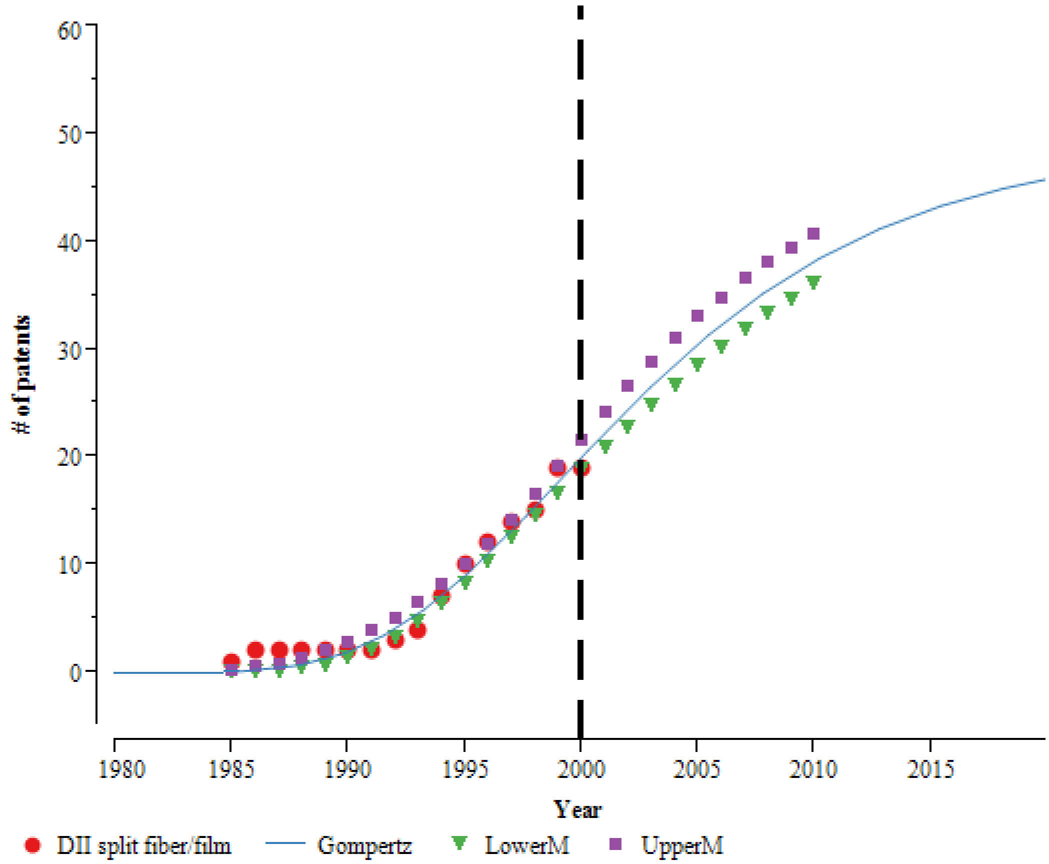

Figure 27. Gompertz model fit for DII split fiber/film data

membranes.

The membrane cumulative data for basic and applied research is significantly different from all of the previous technologies reviewed. As shown in *Figure 28*, there are sharp increases in publications and patents for all three datasets. There is not a clear explanation for why the basic and applied research publications for membranes are much higher than the other technologies reviewed for air filtration media. The forecaster's hypothesis is that the other technologies are specific to nonwoven web formation technologies which up to 2000 were predominately developed within industry and there wasn't much expertise within the academic community. Membranes are researched by the broader engineering and material science community. Based on the cumulative data trends all three datasets show a continued increase in publications and patents related to membranes. The s-curve result, shown in *Figure 29*, has a good fit with an R-square value of .99 and shows the technology in the growth stage. The full JMP report is shown in Appendix B, *Table 47*. The actual limit of patents related to membranes for air filtration is unknown but the model reports a limit of 889. Since the actual limit is unknown and a limit of 400 was added to the model and graphed along with the unlimited curve and confidence limits. Both forecasted trend lines show a sharp increase in patents for 2005 and 2010. Based on both the cumulative and s-curve results membrane technology will continue grow moderately over the next 10 years.

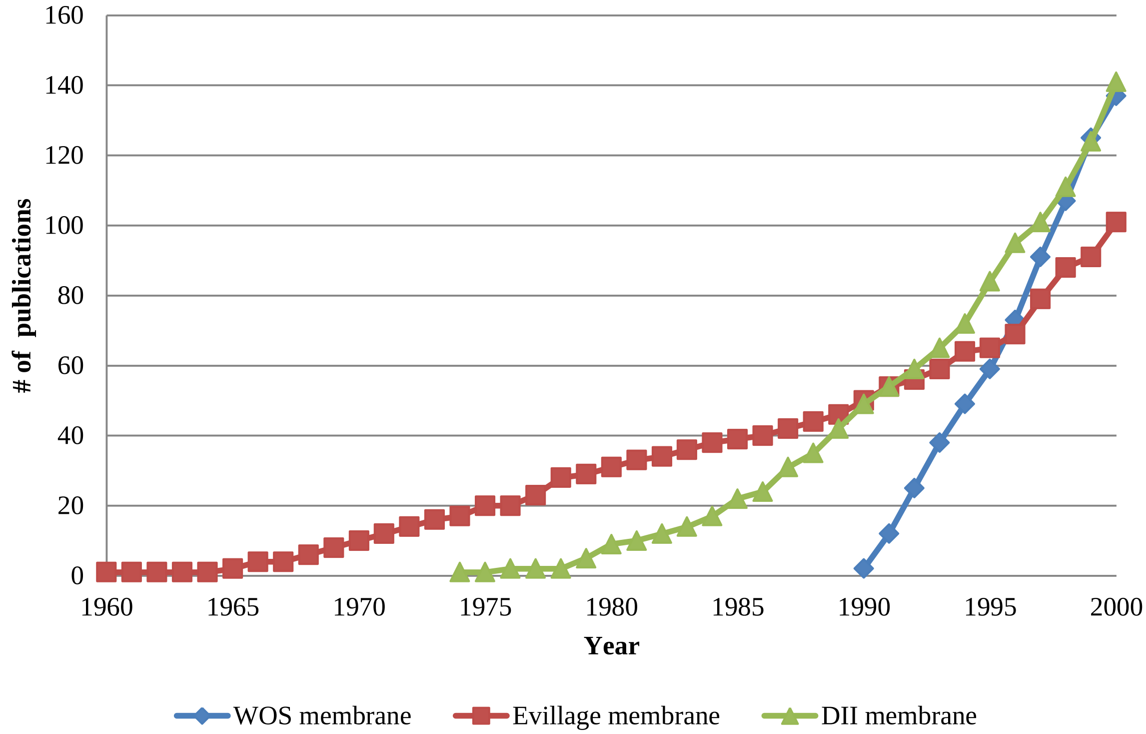

Figure 28. Cumulative membrane publications and patents

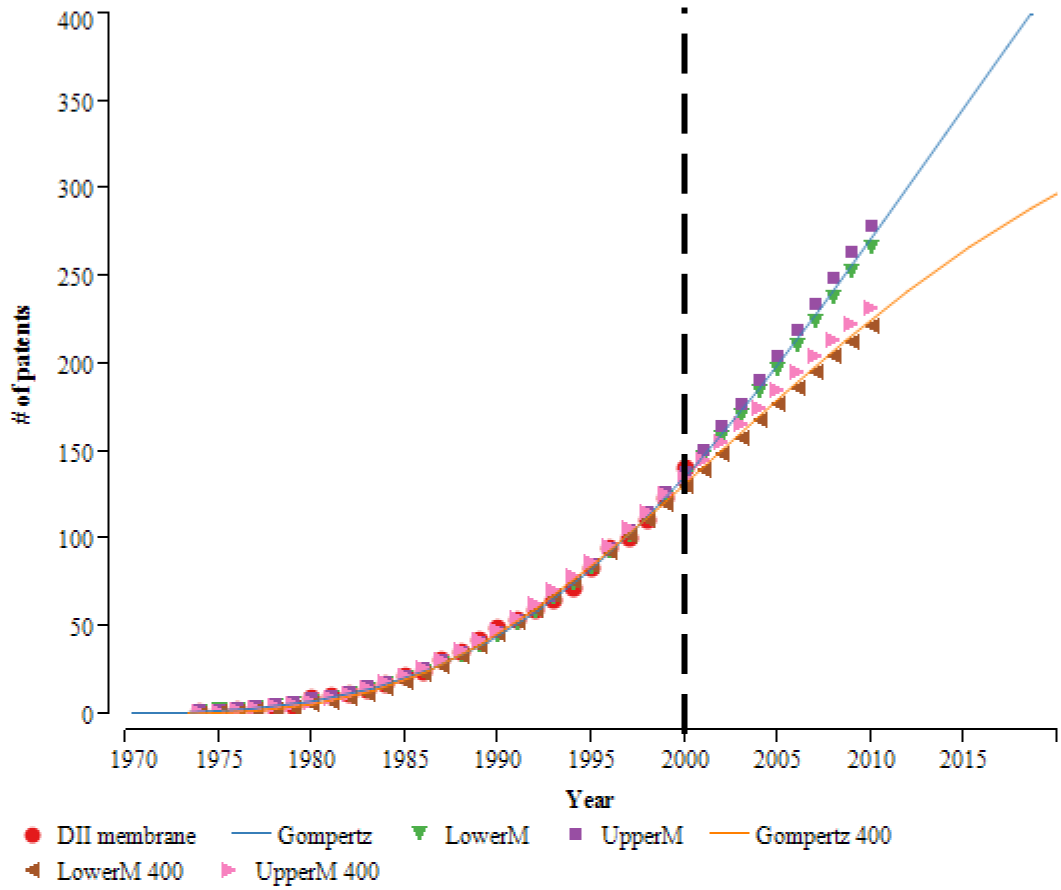

Figure 29. Gompertz model fit for DII membrane data

existing technologies forecast.

All of the technologies were reviewed to address the forecasting questions. It appears from the findings that air filtration media technologies have been developed from within the industry and have received limited attention from basic and applied researchers. The maturity of current technologies were compared and mapped in *Figure 30*. As shown in the illustration, membranes, meltblown, spunbond and split media are in the growth stage and newer technologies. Wetlaid, glass fiber media and needle punch are also in the growth stage but closer to maturity. The cumulative DII datasets for the technologies along with the s-curves were also compared to evaluate which technologies merit the most attention. As shown in *Figure 31*, glass fiber has the largest number of total patents and shows signs of continued growth. Next in terms of total patents and rate of growth are membranes. Needle-punch and meltblowing technologies have the same number of patents but meltblowing appears to be continuing to increase while needle-punch appears to have slowed in growth. Spunbond, split fiber/film and wetlaid technologies have a much lower total number of patents related to air filtration and appear to be in earlier stages of development so it is more challenging to predict how important these technologies will be to air filtration in the future. The forecast statements for each existing technology for 2005 and 2010 are listed in *Table 22*.

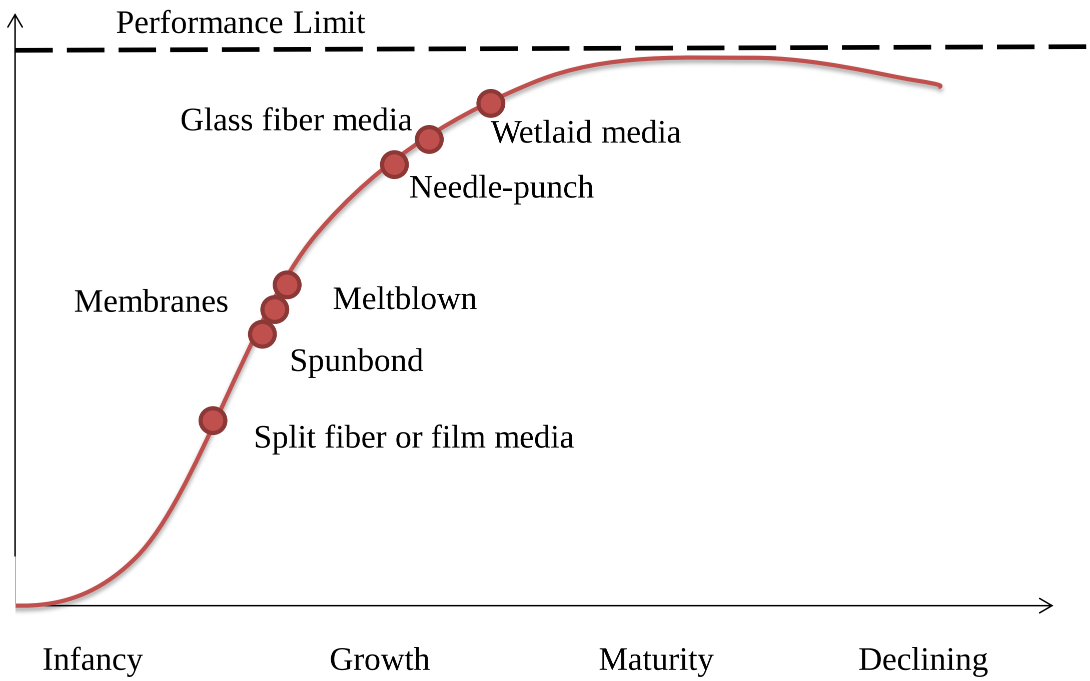

Figure 30. Existing technologies maturity

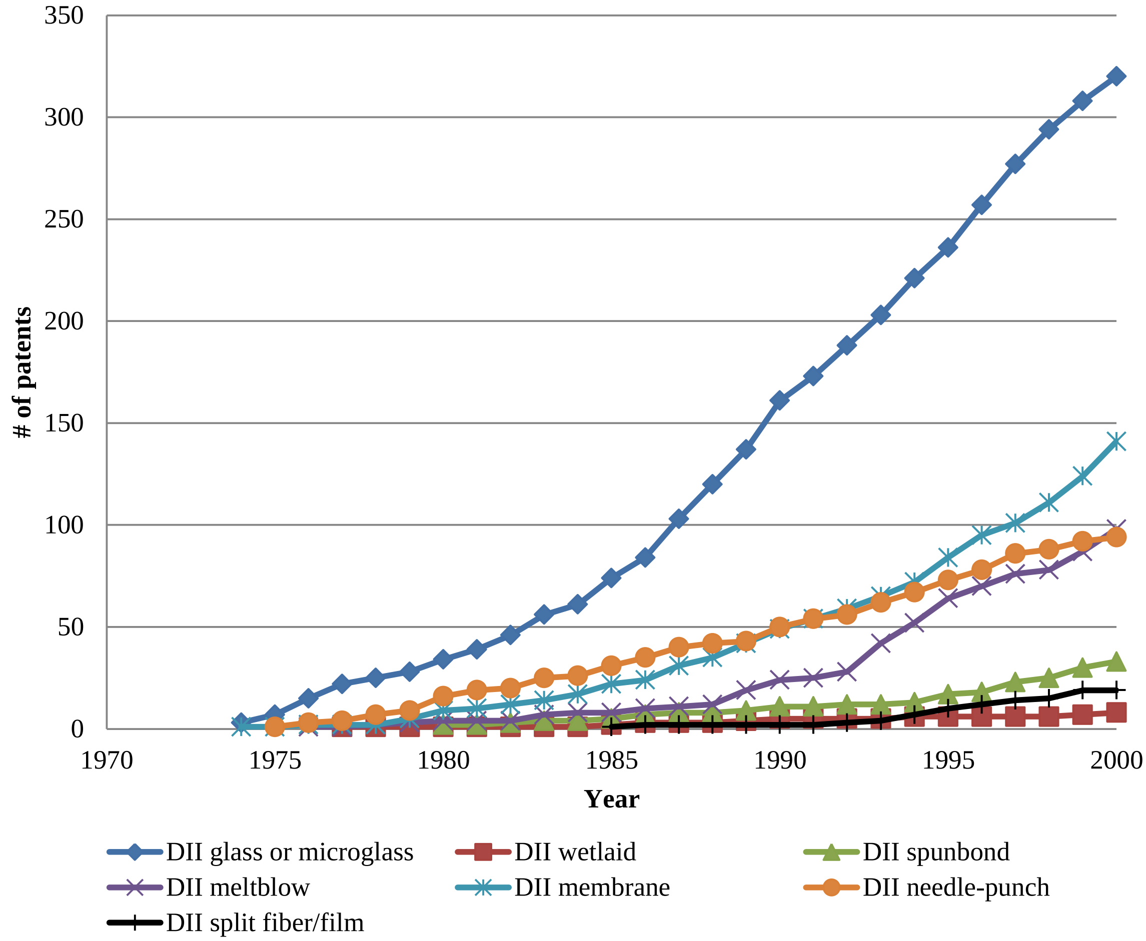

Figure 31. Cumulative DII data for all existing technologies

Table 22. Existing technology forecasts for 2005 and 2010

Technology	Forecast 2005	Forecast 2010
Glass fiber and/or microglass	low growth but remain leading technology in air filtration market	low growth but slowing compared to previous years
Wetlaid	low growth and no new developments in technology but continued use for glass fibers	low growth and no new developments in technology but continued use for glass fibers
Spunbond	moderate growth and increased market share in air filtration market	moderate growth and increased market share in air filtration market
Meltblown	moderate growth and increased market share in air filtration market	moderate growth and increased market share in air filtration market
Needlepunch	low growth but continued use in air filtration media	low growth but continued use in air filtration media
Split film or fiber	low growth but continued use in air filtration media	low growth and but continued use in air filtration media
Membranes	moderate growth and increased market share in air filtration market	moderate growth and increased market share in air filtration market

Existing trends results

The same approached used to represent and forecast existing technologies was used for the existing trends. Each of the existing trend groups were graphed using cumulative publications and patents and the patent datasets were fit to s-curves using the Gompertz growth model.

use of electrostatics.

The use of electrostatics or charging to create electret filters to capture particles was an established trend and technology as of 2000. The cumulative data in *Figure 32* shows there are significantly less basic and applied research publications than patents for the period of 1950-2000. Although the WOS and EVillage publications are lower than the patents there have been significant increases in publications in both areas. Vantage Point was used to review the most cited papers for 1990-2000 in both WOS and EVillage. The WOS articles focused on electrostatic discharge over time, loading performance of charged particles, size capture of electrostatically charge filters, and use of plasma for sterilization of filters. The EVillage articles included the topics of modeling of electret filter media and particle interactions, comparative studies using electret filters and glass fibers, tests comparing the growth of microorganisms, additive and polymer interactions with electrostatics and using in automobiles. According to the graph from 1990 to 2000 there have been approximately 400 patents that mention electrostatics or electret in the abstract. This is a large number of patents and indicates noteworthy level of interests by industry for use of electrostatics in air filtration media. The s-curve result, shown in *Figure 33*, has a good fit with an R-square value of .99 and shows the technology in the growth stage. The full JMP report is shown in Appendix B, *Table 48*. The actual limit of patents related to electrostatics for air filtration is unknown but the model reports a limit of 1804. Since the actual limit is unknown, the data was also fitted with a limit of 1000 and graphed to compare with the unlimited forecast. Both forecasted trend lines show a predicted increase in patents for 2005 and 2010 but the lower limit graph shows a slower rate of growth. Based on both the cumulative and s-curve results, electrostatically charged filter media will continue to grow for 2005 and 2010.

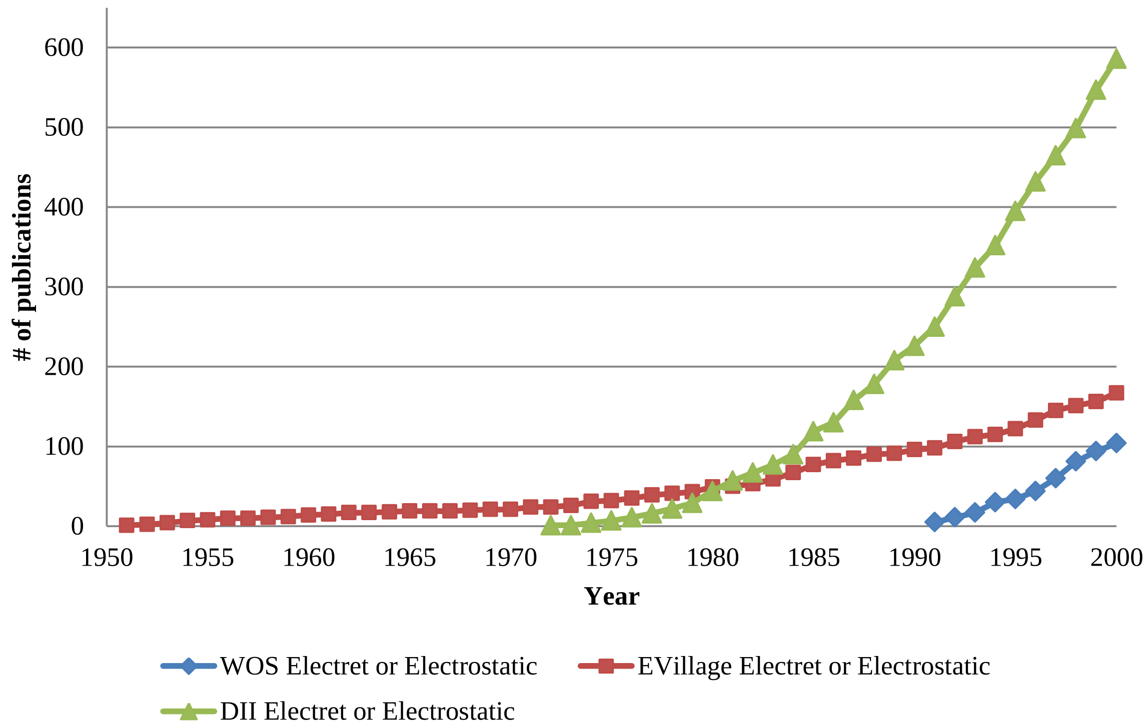

Figure 32. Cumulative electrostatic publications and patents

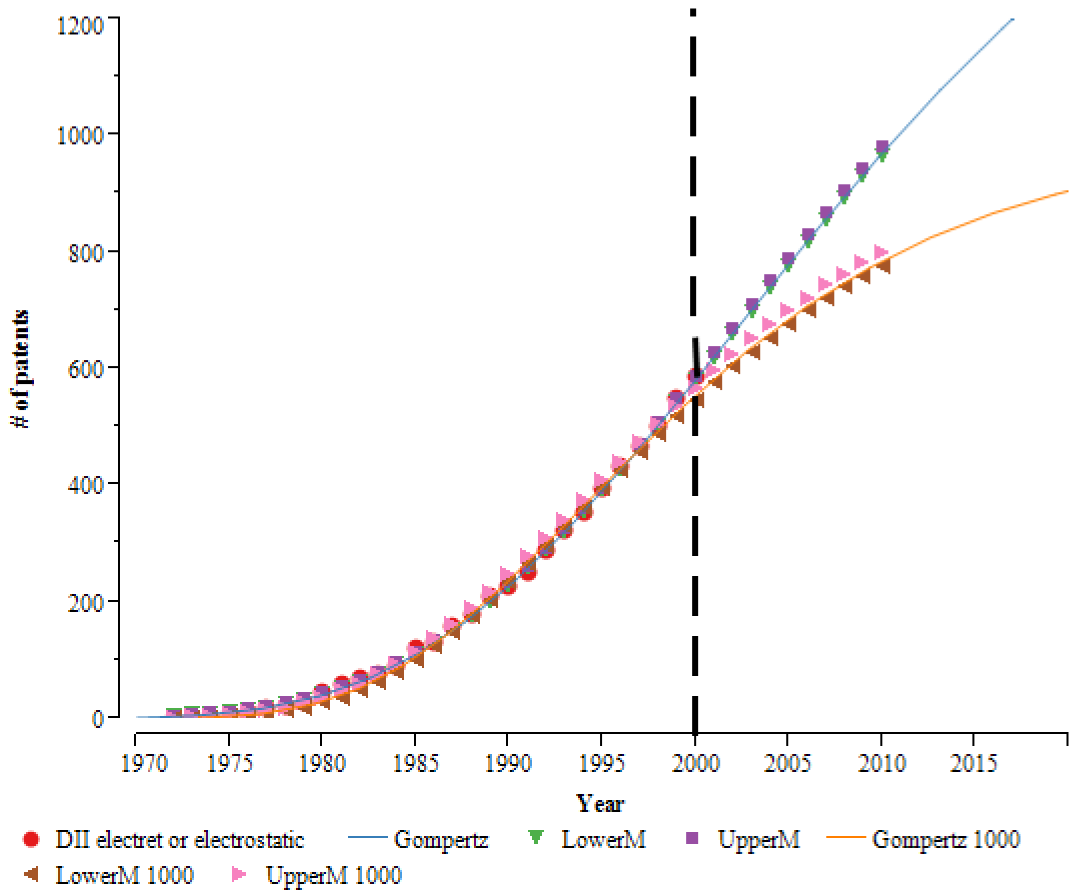

Figure 33. Gompertz model fit for DII electrostatic data

use of composite structures.

The use of composite structures in air filtration media was an established trend as of 2000. In this study composite structures are defined as fiber blends or multi-layered structures. The cumulative data in *Figure 34* shows there are significantly less basic and applied research publications than patents for the period of 1950-2000. There are less than 20 in both WOS and EVillage referring to composite structures. The WOS articles were reviewed and included the following topics; analytical models for composite media, characterization of composite structures/depth filters, use of membranes, and filter caking. The EVillage articles were similar in nature. The composite structure s-curve result, shown in *Figure 35* has a good fit with an R-square value of .99 and shows the technology in the growth stage. The full JMP report is shown in Appendix B, *Table 49*. The actual limit of patents related to composites for air filtration is unknown but the model reports a limit of 8633. Since the actual limit is unknown, the data was also fitted with a limit of 400 and graphed to compare with the unlimited forecast. Both forecasted trend lines show a predicted increase in patents for 2005 and 2010 but the lower limit graph shows the growth rate slowing much sooner than the unlimited forecast. Based on both the cumulative and s-curve results, the use of composites in filter media will continue to grow for 2005 and 2010.

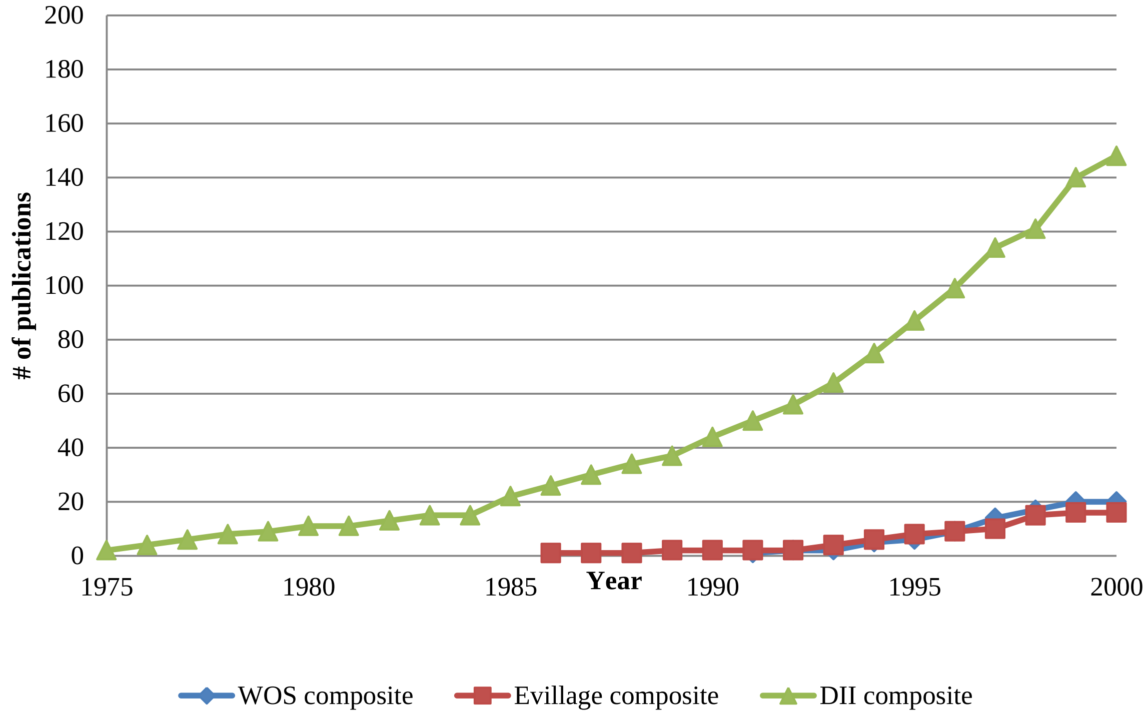

Figure 34. Cumulative composite publications and patents

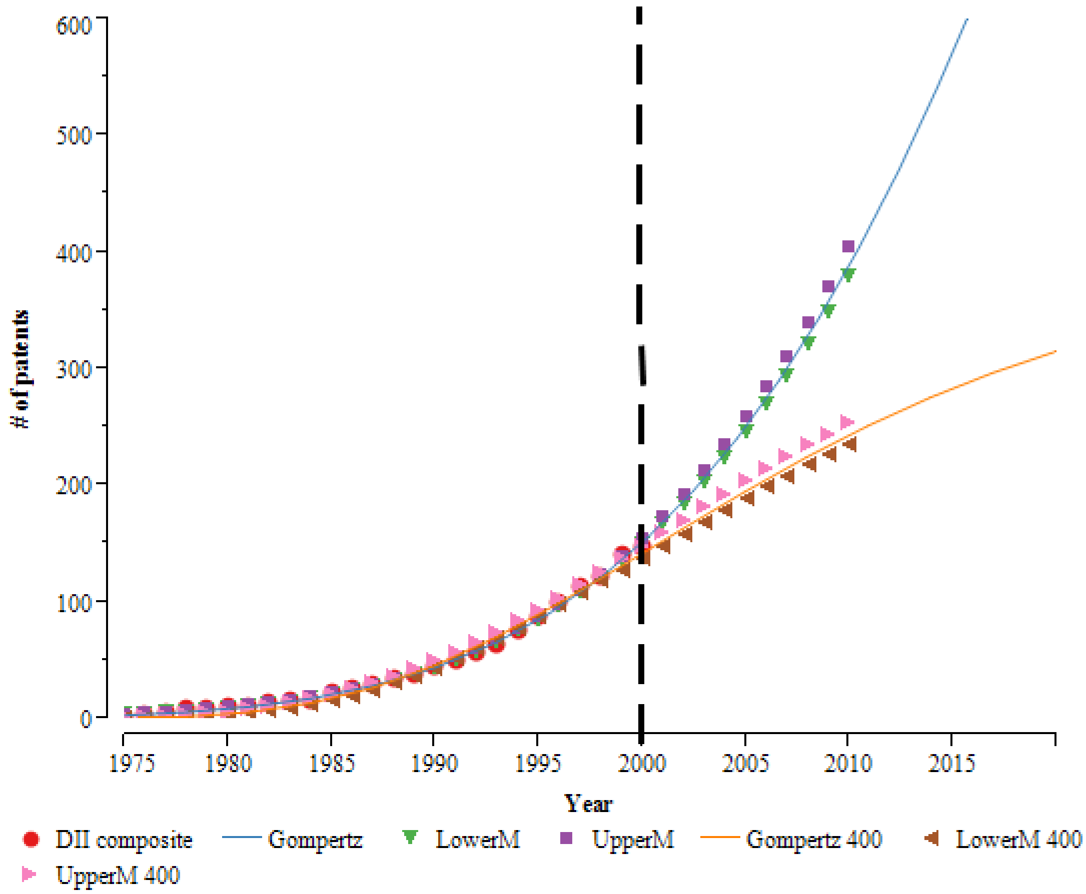

Figure 35. Gompertz model fit for DII composite data

HEPA filtration activity.

The HEPA filtration market was a growing area as of 2000. To forecast the future for the market the cumulative patent and publication data and s-curve for patents were reviewed. The cumulative data in *Figure 36* is shows similar basic and applied research publication trends as other technologies and trends. The WOS articles were reviewed and included the following topics; use of HEPA in hospital and medical applications, various allergens and contaminates, antibacterial filters, HEPA standards, inspection systems, and various respiratory studies. The EVillage articles covered topics on antibacterial, use of pre-filters for HEPA filtration, comparison of filter performance in different environments, and use of electrostatics in HEPA. The HEPA s-curve result, shown in *Figure 37* has a good fit with an R-square value of .99 and shows the technology in the growth stage. The full JMP report is shown in Appendix B, *Table 50*. The actual maximum limit of patents related to HEPA filtration is unknown but the model reports a limit of 2017. Since the actual limit is unknown, the data was also fitted with a limit of 1000 and graphed to compare with the unlimited forecast. Both forecasted trend lines show a predicted increase in growth for 2005 and 2010 but the lower limit graph shows the growth rate slowing sooner than the unlimited forecast. Based on both the cumulative and s-curve results, HEPA filtration activity will continue to grow for 2005 and 2010.

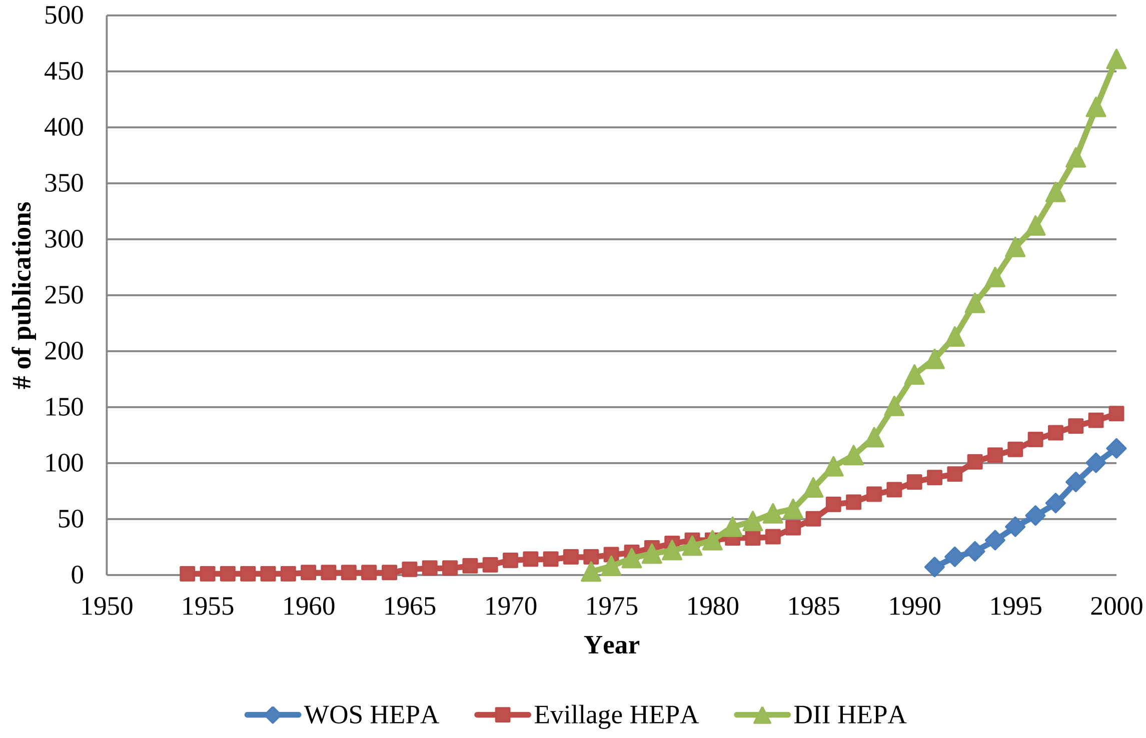

Figure 36. Cumulative HEPA publications and patents

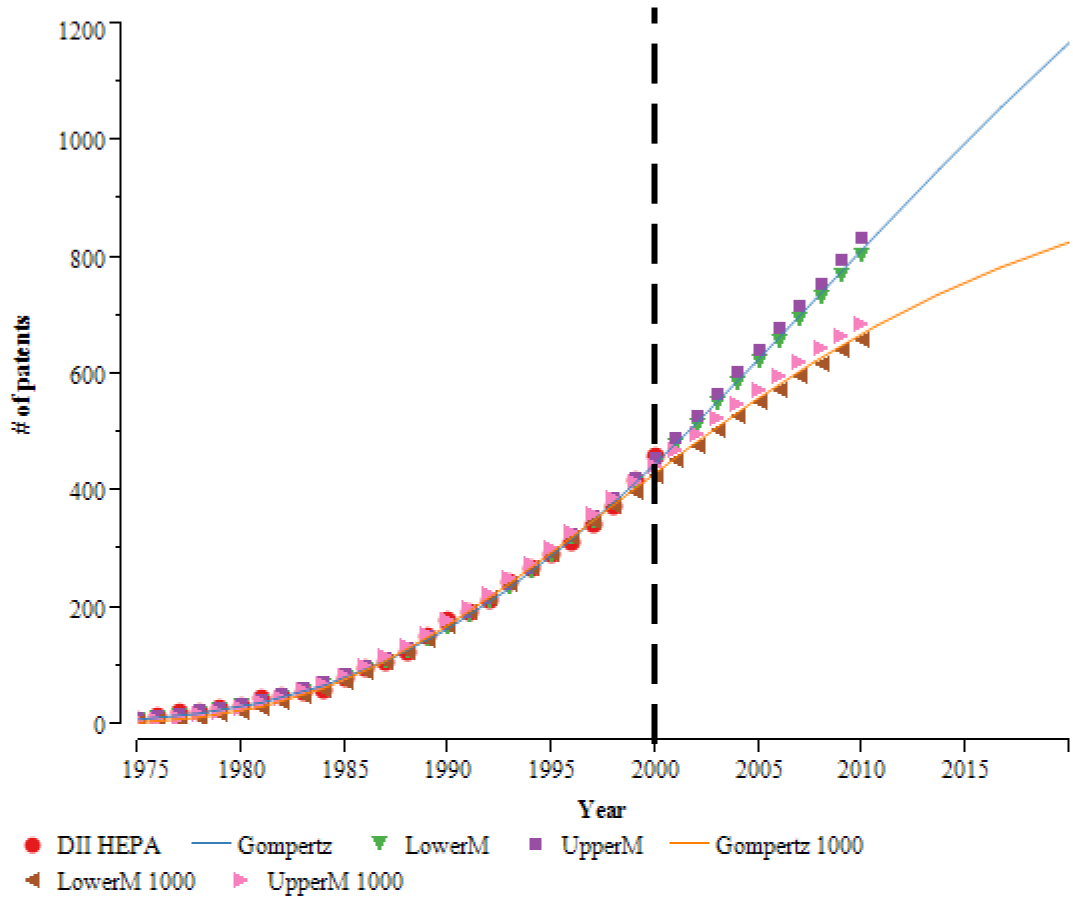

Figure 37. Gompertz model fit for DII HEPA data

existing trends forecast.

All of the trends were reviewed to address the forecasting questions. It appears from the findings that air filtration media trend topics have been primarily addressed in the patents literature and the basic and applied research lags behind invention. The maturity of the trends were compared and mapped in *Figure 38*. As shown in the illustration all three trends are in the growth stage. The cumulative DII datasets and s-curves for the trends were compared to evaluate which technologies merit the most attention. As shown in *Figure 39*, use of electrostatics has the largest number of total patents and shows signs of continued growth. Next in terms of total patents and rate of growth is HEPA filtration activity while the composite trend appears to have slowed in growth. The forecast statements for each existing trend for 2005 and 2010 are listed in *Table 23*.

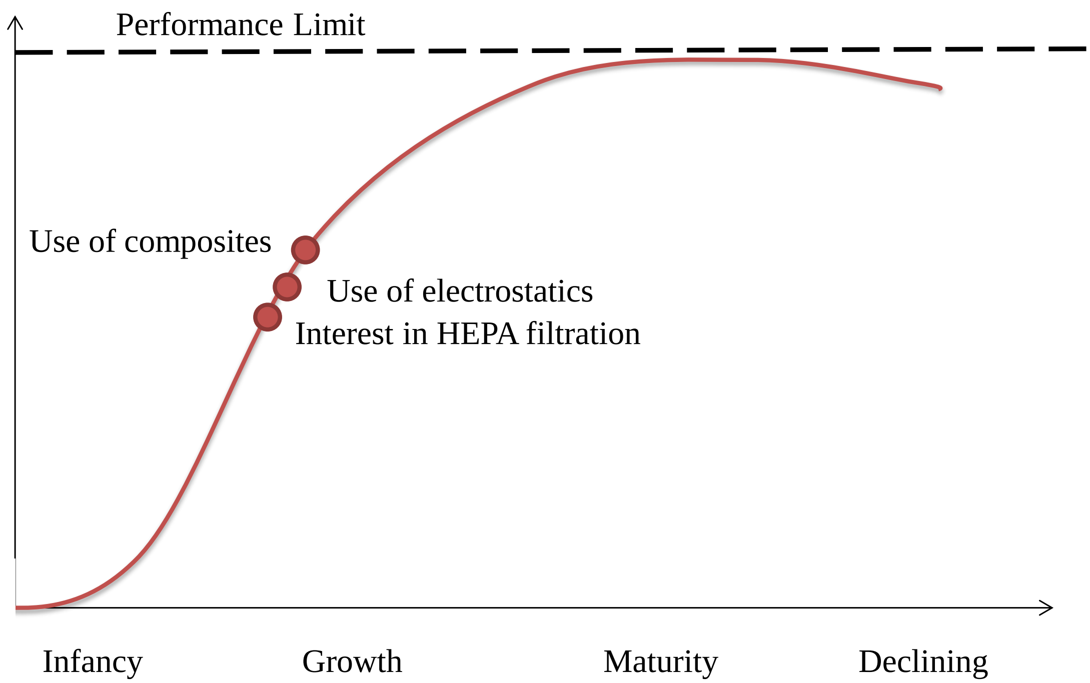

Figure 38. Existing trends maturity

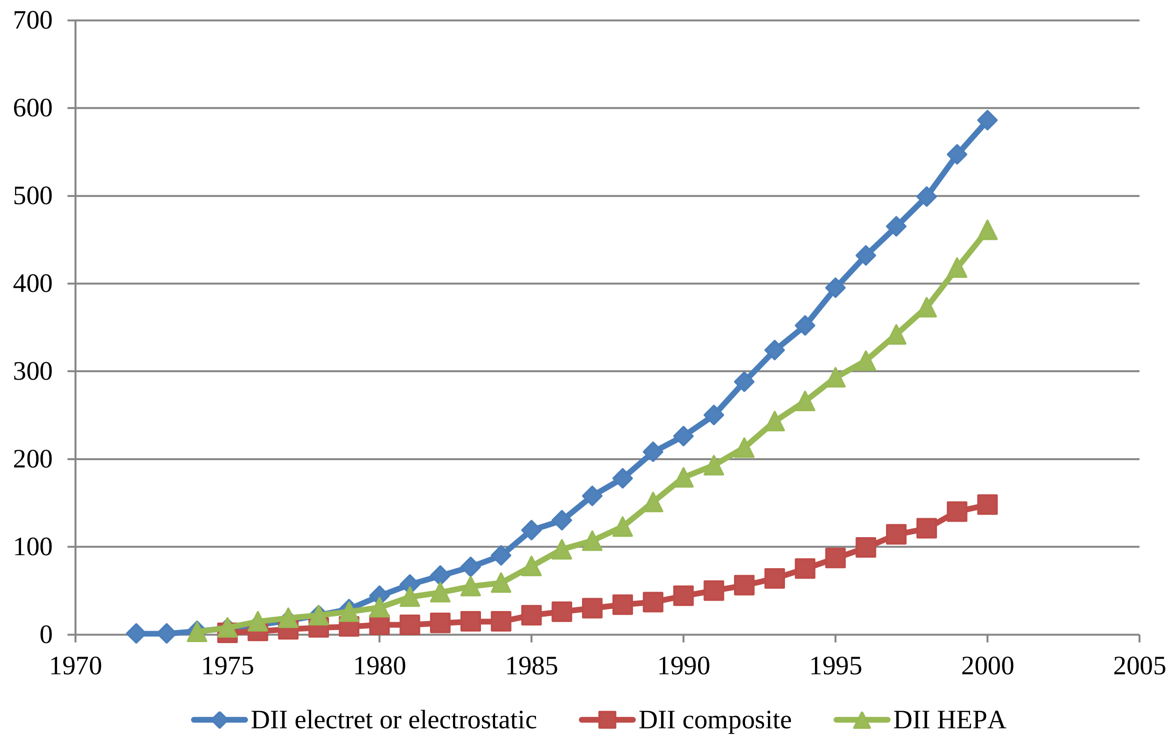

Figure 39. Cumulative DII data for all existing trends

Table 23. Existing trends forecasts for 2005 and 2010

Trend	Forecast 2005	Forecast 2010
Electret or electrostatics	moderate growth and increased market share	moderate growth and increased market share
Composites	low to moderate growth	low to moderate growth
HEPA filtration activity	moderate growth and increased market size	moderate growth and increased market size

Emerging technologies and trends forecast

The emerging technologies and trends were searched and grouped in the same manner as the existing technologies and trends. As shown in *Table 24*, there are very few data points for almost all of the emerging technologies and trends for all of the databases. Due to the limited number of records, trend analysis through graphing of cumulative data and s-curve is not appropriate. Instead, observations about each area were made using Vantage Point as the tool for viewing the records. These observations are listed in *Table 25*. Nanofibers and submicron fibers were included in the original list of emerging technologies but during the analysis nano was also added due to observations in the data.

Table 24. Emerging technology and trend publications and patents by database

	Nanofiber-submicron		Nano			Microfiber*			Antimicrobial			Bicomponent fiber	Self-cleaning*		
Year	WOS	DII	WOS	EV	DII	WOS	EV	DII	WOS	EV	DII	DII	WOS	EV	DII
1985							2								
1986															
1987								1			2			1	
1988								3			1	1			1
1989															1
1990														1	
1991			1					3							
1992			2								1				1
1993			1					1	1		1		1	3	
1994			2	1								1	1	1	
1995			1					1	1	1	1				
1996			2	2				2			2	1	1		
1997		1	4			1		1	3		3		1	2	
1998		1	4	1		1	1		1		5	2		1	1
1999	1	1	4	1	1				2		16	1			1
2000		3	2	2			1	1	1	2	9			2	3

Note. Microfiber indicates there are 2 additional records in EV dataset prior to 1985 and Self-cleaning* indicates there are 11 additional records in EV dataset prior to 1985 and 2 records for DII that are not included in the table.*

Table 25. Emerging technologies and trends forecast

Technology or trend	Observations
Introduction of nanofiber/submicron fibers	Due to the limited references to nanofibers or submicron fibers in the publications and patents related to air filtration, there isn't evidence as of 2000 to show how viable nanofiber technologies will be for air filtration in the 2005 or 2010. The one WOS article discusses the use of electrospinning for formation of nanofibers in air filters. The patents referred to the fibers as submicron fibers instead of nanofibers.
Use of the term nano	The use of the term nano in the WOS and EV datasets were in reference to nano-particles to be filtered out or the use of nano-particles. The one patent refers to a nano-fleece made up of fibers with mean diameter of 10-1000nm.
Use of microfibers	There are few references to microfibers in WOS and EV. The 2 records not shown for EV refer to microfiber glass. The patents describe the use of microfibers in air filters or air filter media.
Antimicrobial functionality	All of the WOS, EV and DII records describe using antimicrobial treatments for air filters. Based on the increase of patents on the topic antimicrobial functionality is a growing area for air filtration.
Use of bicomponent fibers	The bicomponent fibers described in the patents are sheath/core fibers with the sheath having a lower melting point. The fibers are used to bond the media during thermal bonding. Due to the limited data, there isn't evidence as of 2000 to determine if this will be a growing area.
Interest in self-cleaning filters	There are several records in EV and patents in DII referring to self-cleaning characteristics. Most of the records are for use in automotive engines or industrial filtration applications. The self-cleaning actions described are physical in nature for example a pulse that shakes the filter, suction or some other physical force cleans the filter. Based on the publications and patents this is an area of interest but as of 2000 there isn't evidence to determine how much this trend will grow.

TRIZ TF methodology and forecast

TRIZ TF methodology is based on the review of thousands of patents by Altshuller and colleagues. From this review a theory describing how technology evolves was formed which includes a set of common patterns called patterns of evolution. TRIZ TF uses elements from TRIZ problem solving techniques to forecast how technologies might evolve in the future. The common TRIZ TF steps include analysis of the technological system, technology maturity mapping and application of the patterns of evolution. TRIZ TF can be used for normative or exploratory forecasting, but often focuses on what modifications should transpire to take the technology to the next stage in the technology evolution cycle. The resulting forecasts statements are typically qualitative and provide a future direction without reference to timeframe. Following is a detailed description of the implementation of each stage and the forecast results.

Analysis of the technological system

As stated in the literature review, the purpose of the analysis of the technological system is not explicitly described in the literature. The analysis is a form of a literature review or historical account of how the technology has developed over time. By reviewing the development of the technology over time the forecaster gains insight into the solutions employed and may identify patterns of how the technology has evolved. The forecaster also gains information on the problems solved over time and the problems that have yet to be solved. This information will be useful when using the patterns of evolution.

Air filters were first developed in the 1930s to protect the forced-air and heating systems in commercial buildings. They were made from loose mats of animal and synthetic fibers, metal mesh, textiles, and other porous materials. The development of high efficiency filters played a key role in the history of modern day air filtration media. These filters were developed for military application in gas mask canisters to protect individuals from toxic smokes of chemical and biological warfare. Germany developed the first filter media and the material was made of asbestos fiber mixed with esparto pulp. These filters were designed to remove aerosol particles in the submicron range. The United States began to make the same filter media during World War II (1939-1945) through the United States Army Chemical Warfare Service (CWS) and Naval Research Laboratory (NRL) but the media was manufactured by Hollingsworth and Vose Company. After World War II the US Government sponsored research to develop a replacement filter media for the gas mask because the asbestos and esparto fibers were imported from foreign countries. Later the use of asbestos was found to cause health concerns and the material became heavily regulated. In the early 1950s Hollingsworth & Vose Company, Hurlburt Paper Company (no longer incorporated) and Flanders Filters (now known as Flanders-Precisionare) produced a media made from Fiberfax® fibers. Fiberfax® was a ceramic fiber that provided excellent heat resistance but was limited in fiber size so this technology couldn't provide the fine fibers required for high efficiency filtration. (Hutten, 2007)

Arthur D Little is credited with the development of fiberglass in 1931. In the early 1950s he participated in government research to develop a replacement media comprised of glass microfibers which are still used in modern air filtration media. Arthur D. Little founded Cambridge Corporation in 1950; this was the first high efficiency filter manufacturing company. Soon after Cambridge Corporation was founded several other businesses entered the market. Johns Mansville Corporation and Owens Corning Fiberglass Corporation were also pioneers in the development of glass microfibers which ultimately led to fiber diameters as low as 0.2µm. The use of wet-laid and high loft glass and microglass air filtration media dominated the air filtration market until the emergence of synthetic media in the 1980s. As of the year 2000, microglass fiber media still dominated the HEPA market. (Hutten, 2007) also add Lutz Bergmann 2003 and edana 1999.

In 1961 the acronym HEPA (High Efficiency Particulate Air) was used by Humphrey Gilbert in an Atomic Energy Commission report and this acronym has been used ever since. In 1961 HEPA media was defined in standards as being 99.97% efficient against 0.3 µm of dioctyl phthatlate (DOP) smoke. Although HEPA filters originated in military applications and nuclear facilities from the 1960s forward HEPA filters found applications in clean rooms, electronics, pharmaceutical, hospitals, industrial, residences, office buildings, automobiles and even some household appliances.

After the development of fiberglass, the most notable developments in air filtration media were the development of the nonwoven meltblowing and spunbond processes which convert polymer directly into a random laid web. As opposed to other nonwoven technologies these processes form the fiber and fabric in a single process. The development of both technologies began in the early 1950s with meltblowing's origins being the Naval

Research Labs then Exxon while spunbond's development was conducted internally at several fiber companies. The first research and development of meltblowing was done by Van A. Wente of Naval Research laboratories. His concept was to develop fibers from thermoplastic material that were less than 1 micron in diameter for use in filter media. Wente developed a prototype machine that forces molten polymer through a row of fine orifices which is then exposed to two high velocity hot air streams and exist at the nozzle tip. The fibers were then deposited onto a screen. In the early 1970s Exxon took this concept and developed the technology as an application for their polyolefin, polypropylene. Exxon is credited with the naming of the process, multiple publications, large number of patents and helping commercialize it through manufacturing of Tapyrus and licensing it to Kimberly-Clark, Johnson & Johnson, James River, Web Dynamics, Ergon Nonwovens, and 3M along with many others. The meltblowing technology was later licensed to two equipment manufacturers, Accurate Products and Reifenhauser, for the manufacturing of the equipment.

The spunbond technology was simultaneously being developed internally at several companies which resulted in patents from DuPont, Freudenberg, Lurgi, Kimberly-Clark, Monsanto, Ashi and later others. The spunbond process unlike the meltblowing process forms large fibers typically around 20 microns but can be formed up to 50 microns. The process consists of extruding polymer through a die block and into spinnerettes where the fibers are formed and upon existing are quenched with cool air or gas and drawn. The fibers are then randomly deposited onto a moving belt. Because most of the spunbond technology development was conducted internally at companies, the first commercially available spunbond machines weren't available until 1984 from Reifenhauser. Reifenhauser was later joined by Nipon Kodoshi, Kobelco (1997), Hills (1998) and Biax (1998). (Wente, 1956; McCulloch, 1999) In the early 1970s electrostatically charged meltblown webs began development which let to electret filters for use in air filtration. By the 1980s electret filter began taking market share away from the higher cost and higher pressure drop fiberglass media and by 1999, 50% of the North American air filtration market was made of synthetic media which included meltblown and spunbond. (Filter Media Consulting, Inc., 2000).

Application of patterns of evolution

Altshuller's classic patterns of evolution are 8 observed paths along which technologies evolve. Not all of the patterns are relevant to every problem or technology but all of the patterns should be considered. In TRIZ TF the most commonly used patterns are stages of evolution, non-uniform development of system elements and evolution towards increased ideality. The stages of evolution pattern is the basis for the technology maturity mapping process and is always included in a TRIZ TF. The technology maturity mapping process includes collection and evaluation of patents and serves as the foundation of the TRIZ TF. The non-uniform development of system elements pattern has the forecaster break the technology down into subsystem elements to better understand all components affecting the system. In this pattern the forecaster is looking for subsystem elements that may be limiting the system and areas that require further development. The pattern of evolution towards increased ideality could be considered a super-pattern and all of the other patterns are sub-patterns that are moving the technology towards ideality. In this TRIZ TF these 3 patterns are addressed individually while the remaining 5 patterns are discussed in relation to evolution towards increased ideality.

Technology maturity mapping

The primary theory of TRIZ TF is that technological systems go through the same evolution path as biological system, also known as the s-curve. Altshuller's s-curve descriptions of the stages have been modernized into the following four stages infancy, growth, maturity and decline. To determine the maturity of the technology, the forecaster must review patents based on the four descriptive s-curves illustrated in *Figure 40*. Profitability and performance data are not always available; therefore, forecasters often determine the maturity without one or both of these descriptors (Slocum & Lundberg, 2001; Gahide, Clapp, & Slocum, 2000; Lovel, Seastrunk, & Clapp, 2006). The interpretations of the descriptive s-curves are subjective because there are no equations to use to fit the datasets to the curves. The limited papers describing the maturity mapping process add a trend line to the dataset and compare the known dataset to the descriptive s-curve. Therefore, 3^{rd} or 4^{th} order polynomial trend lines were added to the raw data and used to interpret the relationship of the raw data to the descriptive s-curves.

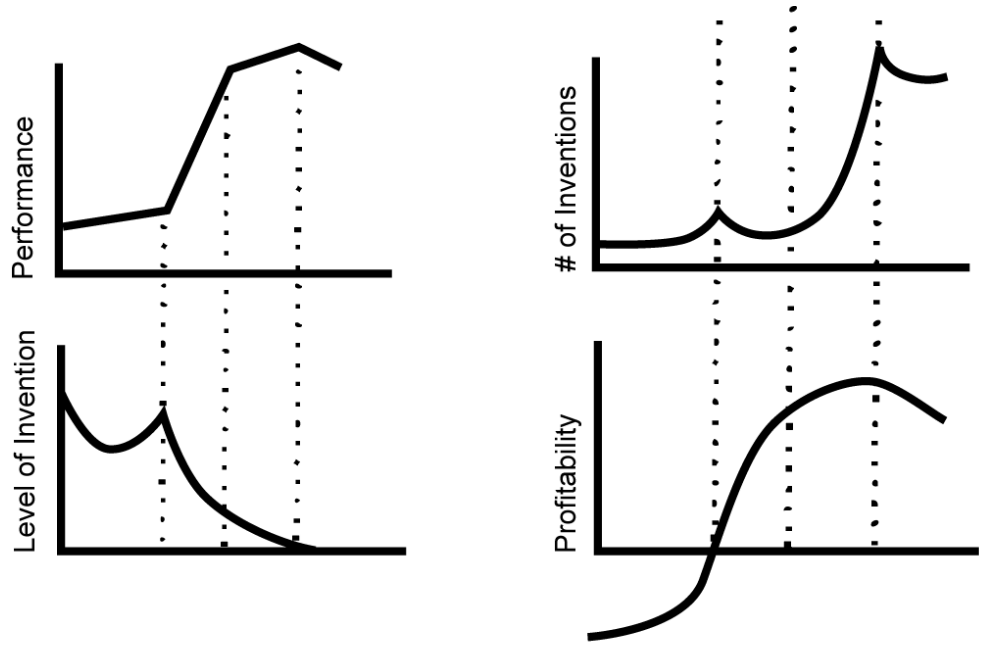

Figure 40: Descriptive s-curves

Note. From *Creativity as an Exact Science* (p. 207) by G., Altshuller, 1984, Amsterdam: Gordon and Breach Publishers. Copyright by 1984 Gordon and Breach Publishers and "The Application of TRIZ to Technology Forecasting A Case Study: Brassiere Strap Technology," by K. Lovel, C. Seastrunk and T. Clapp, 2006, *The TRIZ Journal*, January, p. 6. Retrieved 11 1, 2008, http://www.triz-journal.com/archives/2006/01/09.pdf, Copyright 2006 by *The TRIZ Journal*.

patent search.

In TRIZ TF patent analysis serves as the primary source for determining maturity. The same patents used in the tech mining portion of the study were used for the TRIZ TF. The development of the level of invention (LOI) s-curve requires the forecaster to review patents based on Altshuller's 5 levels of invention and rate them. The levels, descriptions and typical percentages of patents for each level are shown in *Table 26*. The patent search resulted in 3,612 total records. The review of all of the patents would take a significant amount of time, so it was determined a more practical approach would be to select a portion of the patents for review. To narrow the patents to a readable number it was calculated that 364 patents, be included in the sample with a 95% confidence level. A stratified sampling process was used to select the patents. First, VantagePoint was used to identify the most frequently cited patents. The theory for selecting the most cited patents is these would most likely be the foundation patents and rate as a 4 or 5 for LOI. The most cited patents were the top 12 which were cited 47-21 times. A second group of 58 highly cited patents was identified and these had 19-10 citations. A total of 70 highly cited patents were identified. Based on Altshuller's expected percentages for level 4-5, as shown *Table 26*, 5% of the patents should be ranked as 4-5 which would be 180 out of the 3612 total patents. Since only 70 highly cited patents were identified, all of these were used in the study. To select the remaining patents it was important that each patent year be accurately represented, so 10% of the total number of patents in each year was calculated. Then the years were identified for the 70 highly cited patents and remaining patents from each year were randomly selected until the total sample size was 364. The random selection was performed by a custom program developed to read the patent numbers from a text file shuffle the patents and extract 10% of the remaining patents for each year.

number of inventions.

The number of inventions over time s-curve is relatively simple to acquire. Derwent Innovation Index (DII) was used to retrieve the patent dataset. The cumulative number of patents granted per year was graphed from 1967-2000. The results are shown in *Figure 41*. When compared to the descriptive s-curve in *Figure 42*, the dataset appears to be in the portion of the graph highlighted by the blue rectangle.

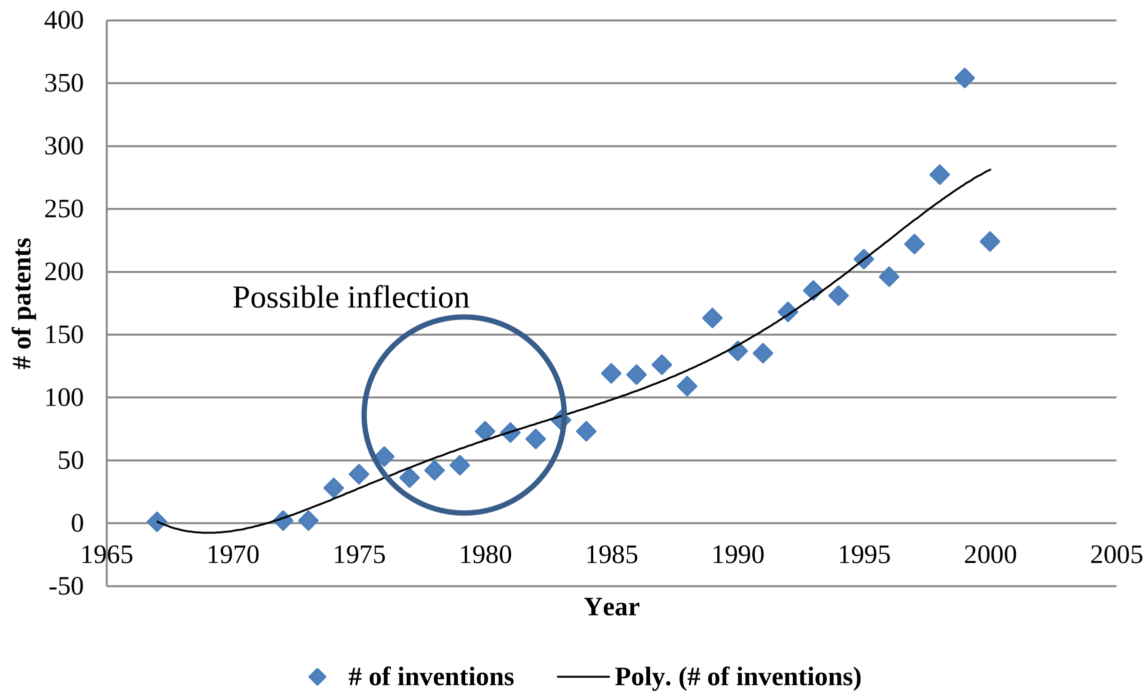

Figure 41. Number of inventions data

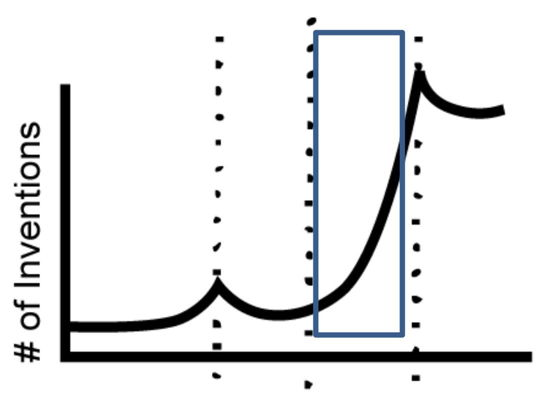

Figure 42. Number of inventions s-curve

rating patents for level of invention.

The rating of the patents for level of invention (LOI) was the most time consuming portion of the study. A total of 364 patents were reviewed using the criterion defined for Altshuller's 5 levels of invention. The levels, descriptions and typical percentages of patents for each level are shown in *Table 26*. The highly cited patents were reviewed first and the full patents were used for evaluating LOI. A majority of the patents could be viewed through the DII database but some patents were downloaded from the US Patent and Trademark Office. Foreign patents were included in the rating process but a majority of the Japanese patents were only patented in Japan so English versions of the full patents weren't available for review. It was decided to include the Japanese patents in the review since Japan accounted for 49% of the total patents from 1967-2000. In these 97 cases the DII detailed record and abstract was used to evaluate the patent for LOI. Since the full patents weren't available for review of these Japanese patents there is some level of bias in these ratings.

Table 26. Five levels of invention

Level of invention	Description	Percentage of patents
1	Apparent/conventional solution	32%
2	Improvement	45%
3	Substantial invention inside technology	18%
4	Invention outside technology	4%
5	Discovery	1%

The patent information and results needed to be stored in a database so Vantage Point was used to group the patent sample and a new dataset was created from the group. Next a user defined record classification for the LOI was added to the record field. Within Vantage Point each record was classified for LOI using the record classification as shown in the record display in *Figure 43*. After all of the patents were evaluated, the data was exported in a file format compatible with Microsoft Excel for further analysis and interpretation. The complete results of LOI ratings are listed in Appendix B, *Table 51*.

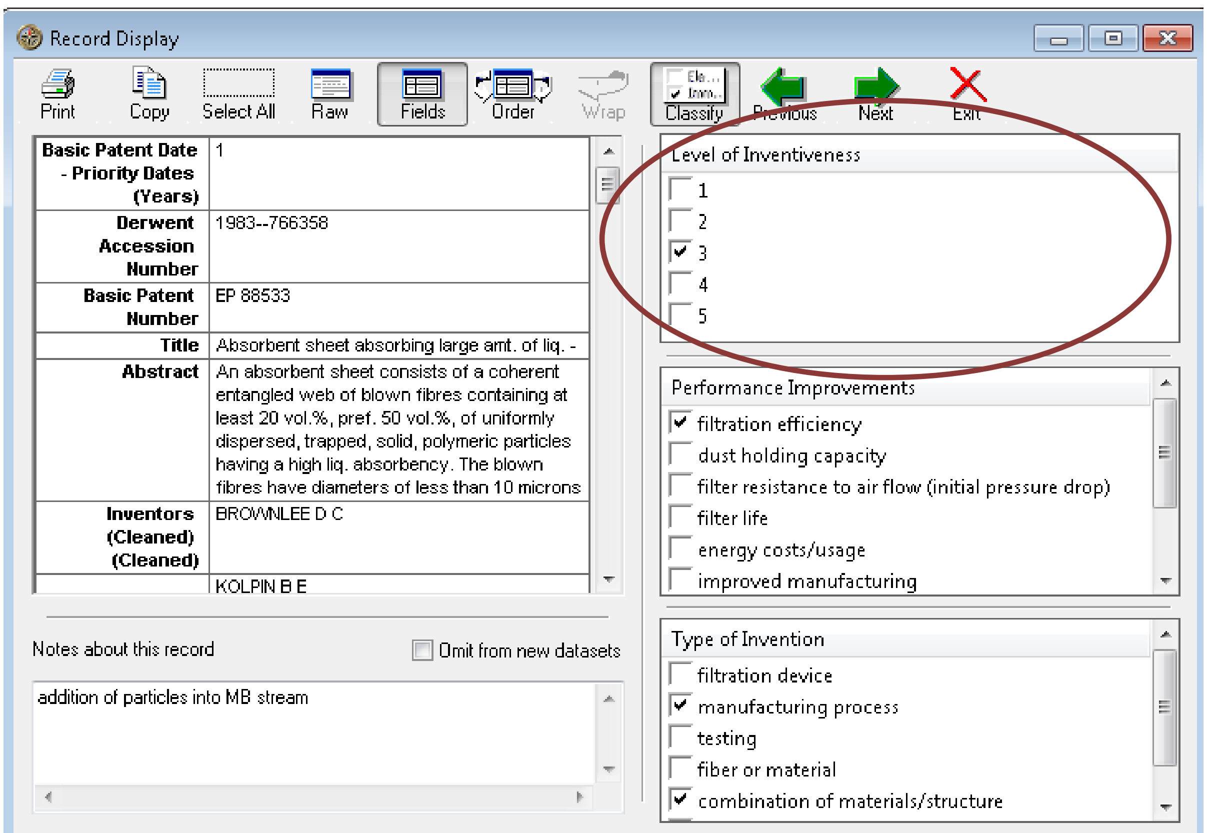

Figure 43. Vantage Point screen shot of individual record display, LOI

To begin the analysis the percentages for each level of invention (LOI) was calculated and compared to the expected percentages. As shown in *Table 27* the results of the study were close to the expected values with the exception of the percentage of patents falling into level 1. The study results were 12% higher in ratings for level 1. The next step was to plot the LOI s-curve. As demonstrated in the literature this was done by averaging the LOI for each year and plotting the results over the time period. The resulting LOI s-curve is shown in *Figure 44*. A polynomial trend line was added to help interpret the dataset. As illustrated in the previous s-curve, number of inventions, the number of patents for a technology typically increases over time; therefore, calculating the average LOI for each year would potentially cover up higher level inventions. One additional graph was added to high-light the level 4 and 5 LOI patents over the time period. The graph is shown in *Figure 45*. When both graphs are compared to the LOI s-curve in *Figure 46*, the dataset appears to fall within the second or third stage as illustrated by the blue rectangle. Using this graph alone there isn't enough information to say if the dataset is best represented by either the second or third stage of the LOI s-curve.

Table 27. Comparison of expected LOI percentages to study results

Level of invention	Description	Expected percentages	Results for study
1	Apparent/conventional solution	32%	44%
2	Improvement	45%	41%
3	Substantial invention inside technology	18%	12%
4	Invention outside technology	4%	3%
5	Discovery	1%	0%

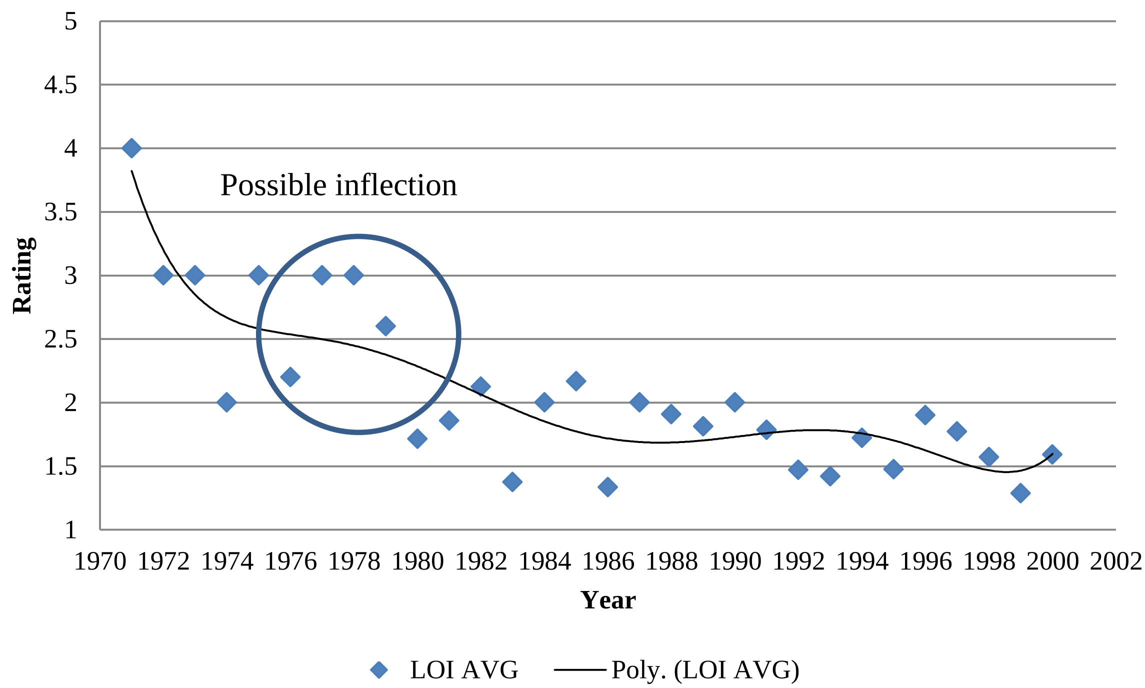

Figure 44. Level of invention data

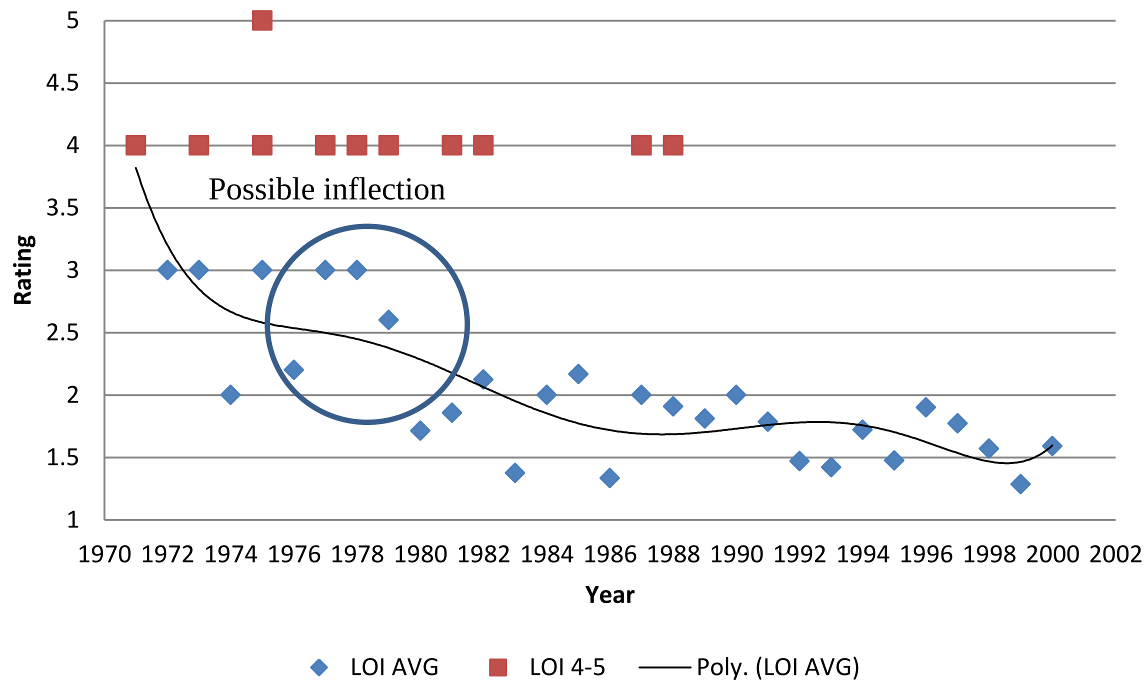

Figure 45. Level of invention average and 4 & 5 ratings

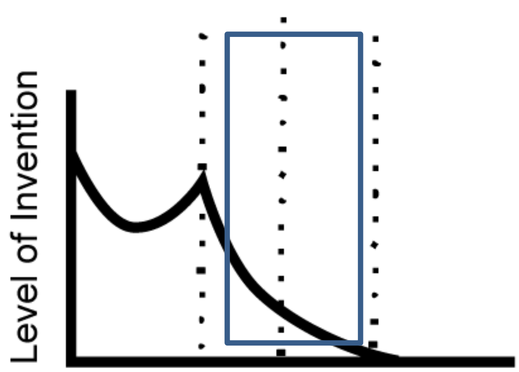

Figure 46. Level of invention s-curve

profitability.

The profitability data was challenging to retrieve due to the historic time period used in the study. It was difficult to find data from a single, consistent source over a significant period of time. With the increase in digital information since the early 1990s, finding profitability data for a forecasting study conducted today should be easier. Ultimately, the data was retrieved from INDA's market report, *Analysis, The Nonwovens Industry in North America* (INDA, 2000). The data was reported as an average annual growth rate (AAGR) from 1993-1998. When compared to the profitability s-curve in *Figure 48*. The data appears to fall within the third stage of the curve. The data appears to be increasing at a steady rate but slower than the rate of change illustrated in the second stage of the descriptive s-curve.

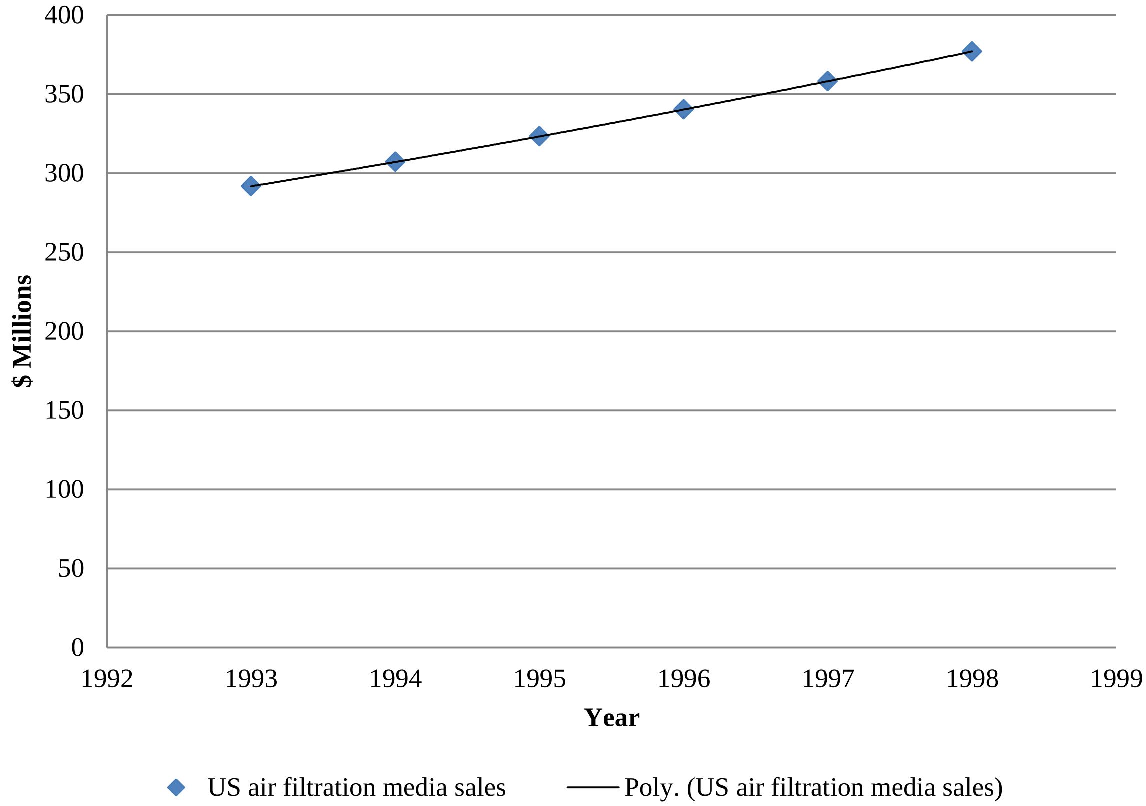

Figure 47. Profitability data

Note. Data from *Analysis The Nonwovens Industry in North America* Cary, NC: INDA. Copyright 2000 by INDA, Association of the Nonwoven Fabrics Industry.

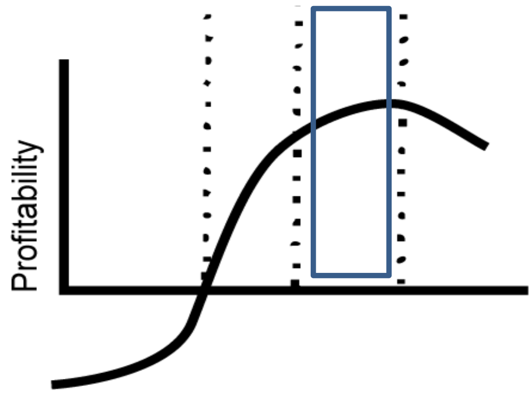

Figure 48. Profitability s-curve

performance.

There are many technologies that contribute to air filtration media so there isn't a single technology that could be used to measure performance. There are also several performance measures for air filtration media but these aren't typically published and when they are published they are measured through different metrics making it difficult to compare over time. For these reasons there is no performance curve used in this study. One note should be made that since the 1960s the definition of HEPA filtration has been 0.3 µm particles with 99.97% collection efficiency and ULPA filtration has been defined as .12 µm particles with 99.999% collection efficiency.

maturity.

The maturity of a technology or system is determined by reviewing each of the descriptive s-curves and identifying the maturity level. The three descriptive s-curves used in the study are shown in *Figure 49*. The forecaster's interpretation of the dataset for maturity in each s-curve is identified by the blue rectangles. Based on the review of the descriptive s-curves, air filtration media appears to be at the beginning of the maturity stage as indicated in *Figure 50*. Since air filtration media is not a single technology but rather consists of multiple technologies that come together to create the media, this can be interpreted to mean the current technologies used in air filtration media are maturing. Often when other technologies are maturing, new technology s-curves begin. Using the level of invention rating as of 2000 as an indicator, there hasn't been a new breakthrough invention for air filtration media at this time that should be watched. Over the next 5-10 years R&D should be looking for the next breakthrough invention(s). The future directions for air filtration media can be further understood through the application of the patterns of evolution.

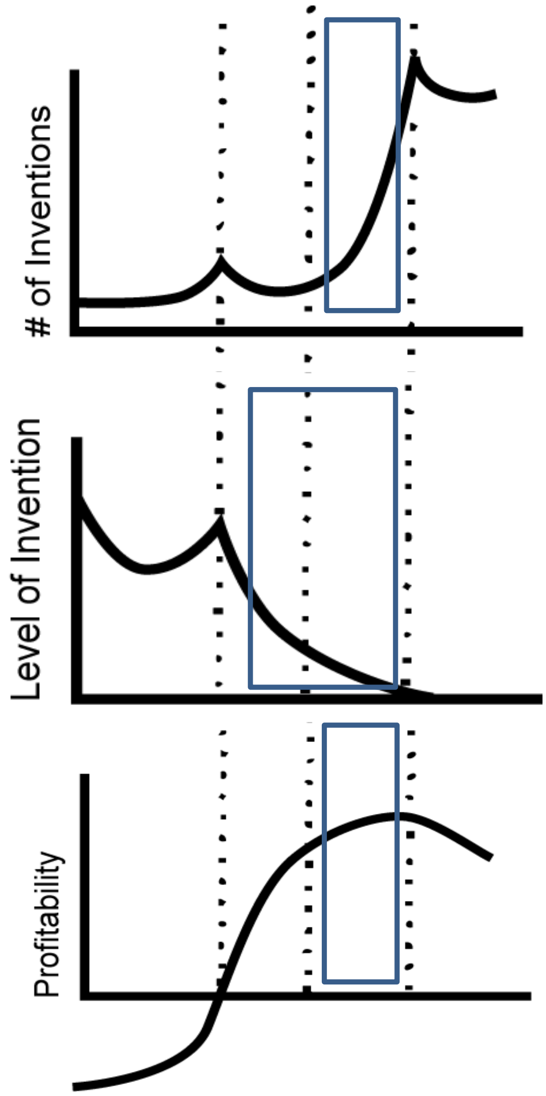

Figure 49. All descriptive s-curves

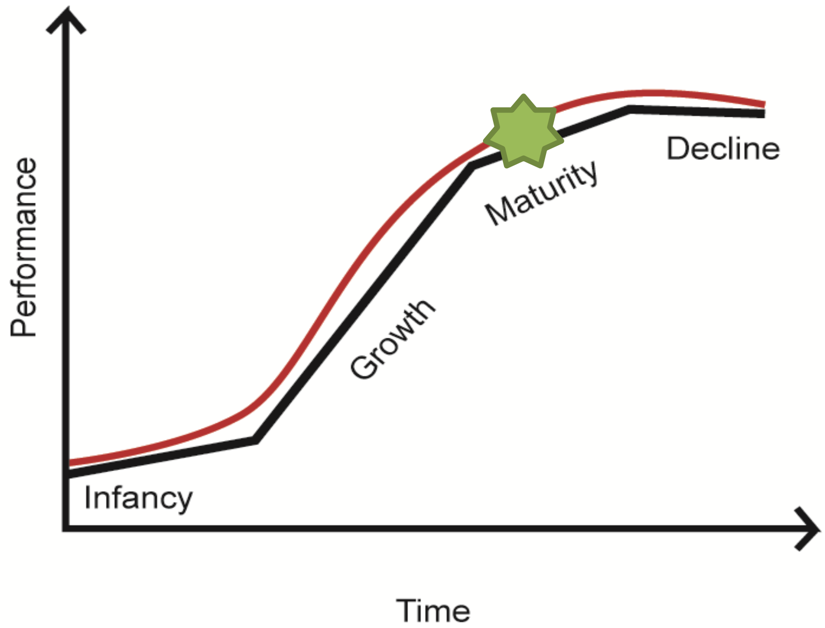

Figure 50. Maturity for air filtration media

Non-uniform development of system elements

The pattern of non-uniform development of system elements is based on the theory that a technology system is made up multiple components and these have their own s-curves. This non-uniformity can cause constraints and contradictions within the technology system that prevent progress. According to the literature a TRIZ practitioner can analyze a system's elements to identify constraining components (Silverstien, DeCarlo, & Slocum, 2005). An illustration of the systems approach model for air filtration media is shown in *Figure 51*. In this study for the first time the same patents that were evaluated for LOI were also classified as a system element. A user defined record classification for system elements was added to the record field in the same manner as the LOI record classification. The additional classification was added to gain insight into the s-curves of the system elements. The list of system elements are shown in *Table 28*. The system element filtration device is actually the super-system for air filtration media but was included to make sure all patent inventions were adequately represented. After all of the patents were evaluated, the data was exported in a file format compatible with Microsoft Excel for further analysis and interpretation. Patents were often classified as more than one system element and when the data was analyzed the patents were counted in all the groups they were classified in. The complete results of system elements classifications are listed in Appendix A, *Table 51*.

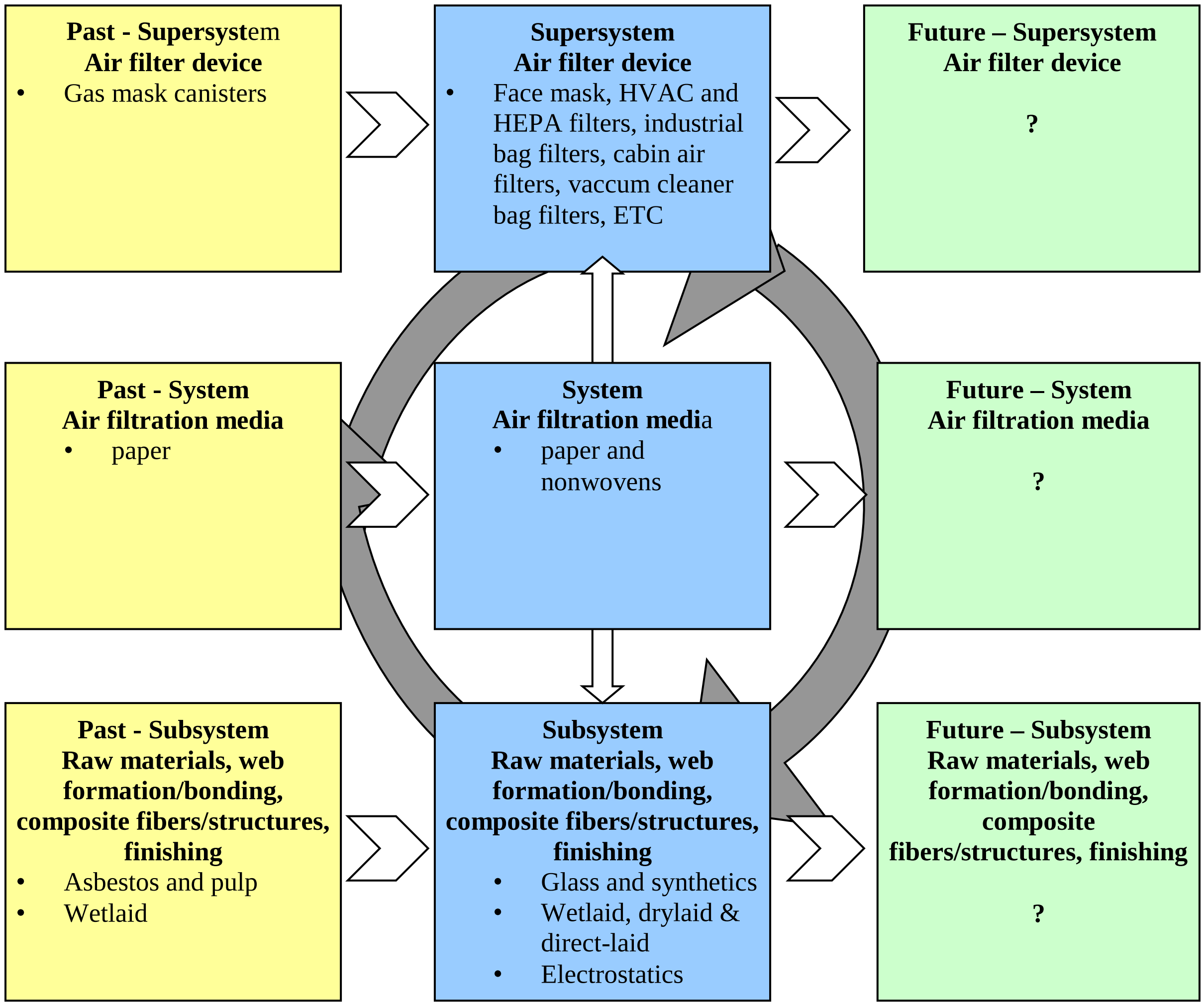

Figure 51. Air filtration media systems approach model

Table 28. Air filtration media system elements

System element	System classification
Raw material	Subsystem
Web formation/bonding	Subsystem
Composite of fibers/structure	Subsystem
Finishing	Subsystem
Filtration device	Super-system

To begin the cumulative data for total number of patents classified in each system element group were compared over time. The graph in *Figure 52* shows the system element composite of fibers/structure with the most patents and the most significant rate of change. The super system element, filtration device, also appears to be more developed than raw materials, web formation/bonding and finishing elements. Based on the cumulative growth it appears developments in all system elements are increasing with the exception of web formation/bonding and finishing which appear to have leveled off.

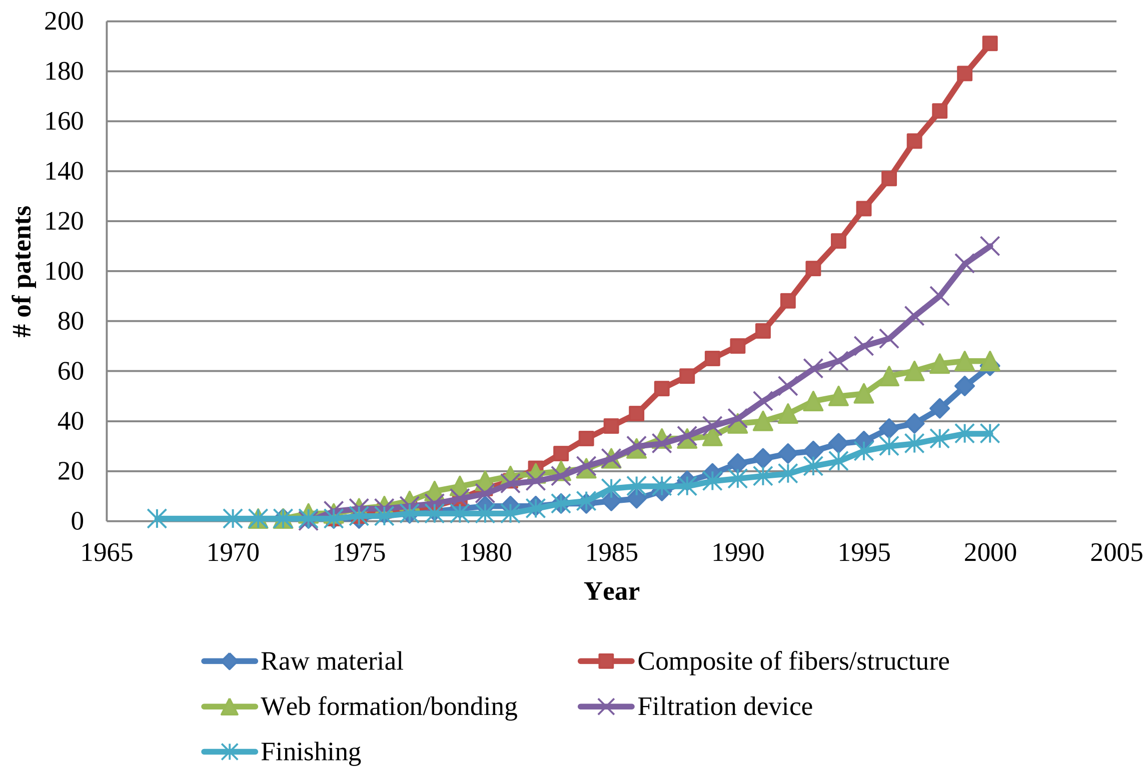

Figure 52. All system elements number of patents over time

Next each system element was evaluated for maturity based on the number of inventions and LOI s-curves. The cumulative number of patents granted per year was graphed from 1970-2000. As previously mentioned there are no equations to use to fit the data to the number of inventions or LOI s-curves; therefore, polynomial trend lines were added to help interpret the trend in the dataset.

raw material.

The raw material number of inventions data is shown in *Figure 53*. When compared to the descriptive s-curve in *Figure 54,* it is difficult to put the subsystem in a single stage of development. The dataset appears to be in the portion of the graph highlighted by the blue rectangle which includes both the growth and maturity stages. To determine the LOI maturity the average LOI for each year and plotted over the time. The resulting raw material LOI data is shown in *Figure 55*. When the LOI data is compared to the LOI s-curve in *Figure 56* the system element appears to be in the second stage, growth. Both descriptive s-curves were used to evaluate the maturity of raw material element and determined it is in the growth stage. Considering the maturity and the limited number of patents in the area compared to other system elements there is opportunity for new technology development in the area of raw materials.

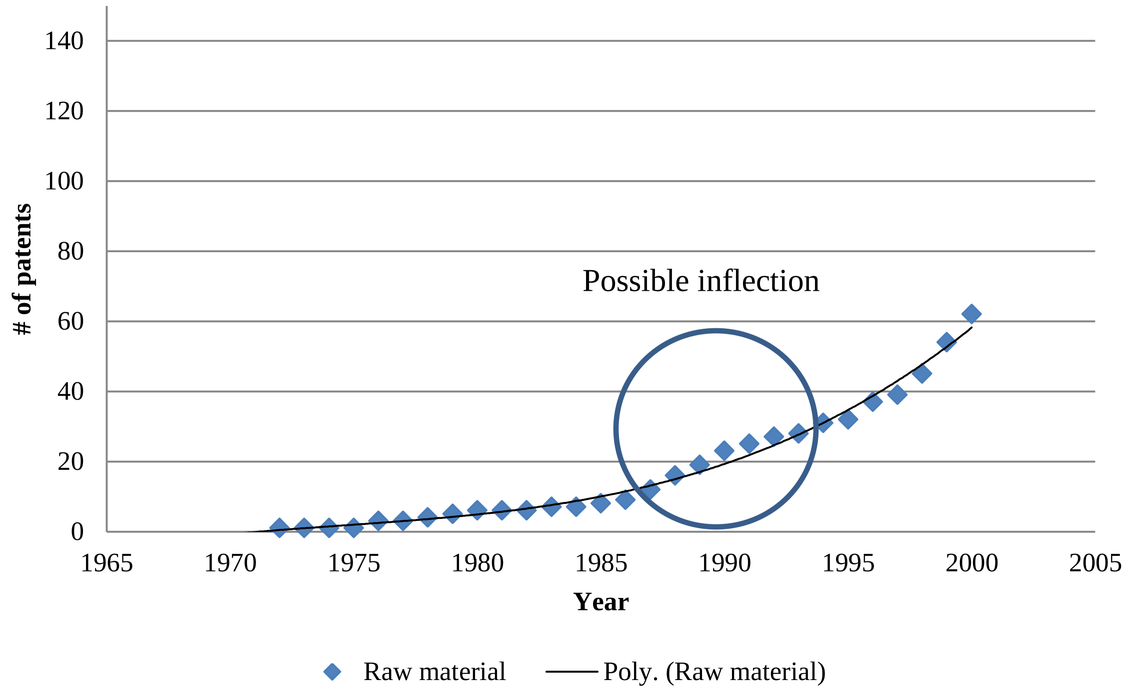

Figure 53. Raw material number of inventions data

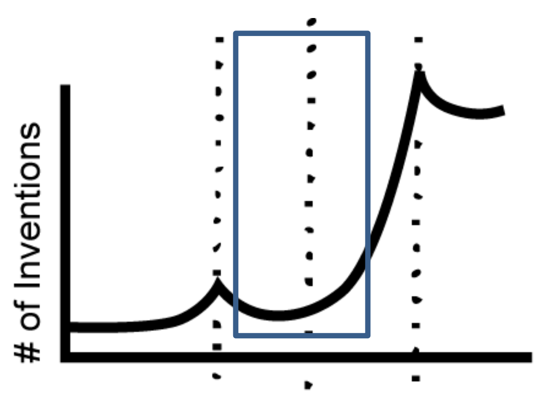

Figure 54. Raw material number of inventions s-curve

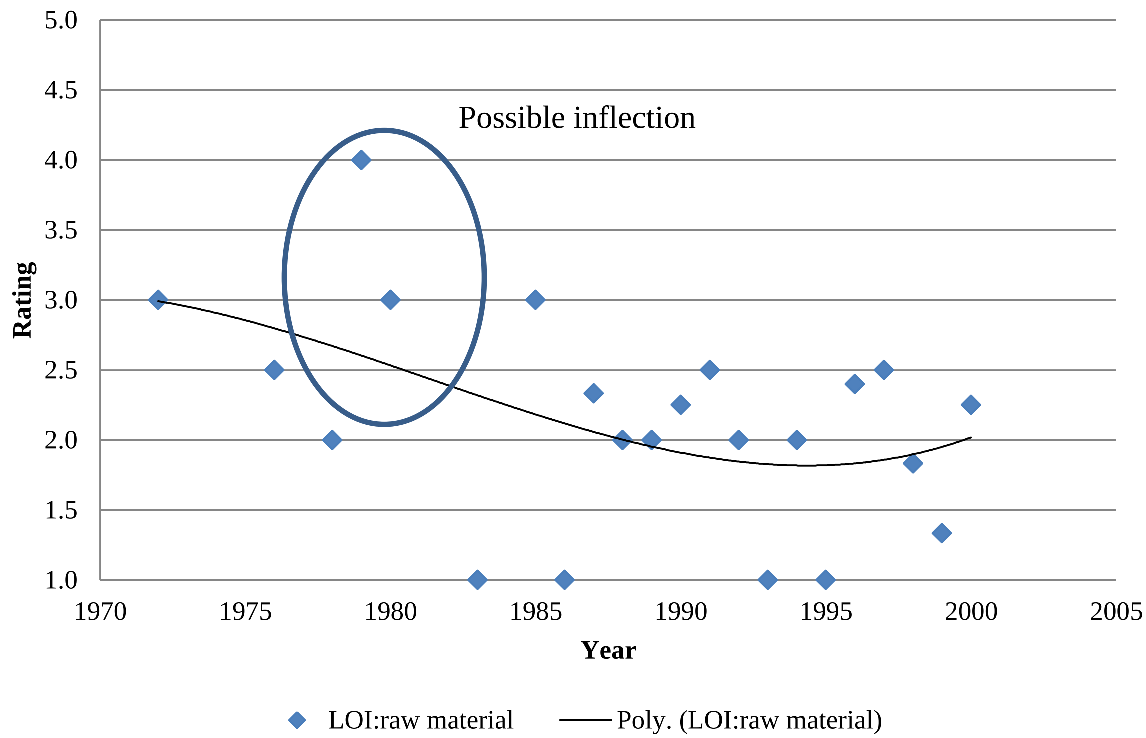

Figure 55. Raw material level of invention data

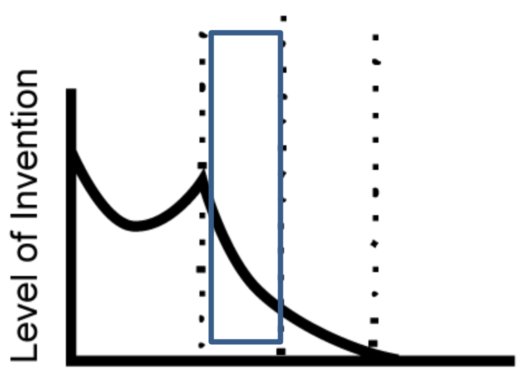

Figure 56. Raw material level of invention s-curve

composite of fibers/structure.

The composite of fibers/structure number of inventions data is shown in *Figure 57*. When compared to the descriptive s-curve in *Figure 58,* the dataset appears to be in the portion of the graph highlighted by the red rectangle which is the third stage, maturity. There isn't an obvious inflection point in the dataset but the steepness of the curve indicates the subsystem is in the third stage. The LOI data results are shown in *Figure 59*. When the LOI data is compared to the LOI s-curve in *Figure 60*, it is difficult to place the subsystem element in a single stage of development. The system element appears to be in either the growth or maturity stage as indicated by the red rectangle. Both descriptive s-curves were used to evaluate the maturity of composite of fibers/structure element and determined it's in the early maturity stage. Considering the maturity and the large number of patents in the area compared to other system elements, this system element may be reaching a limit and one of the other elements should be further developed to help air filtration media move forward.

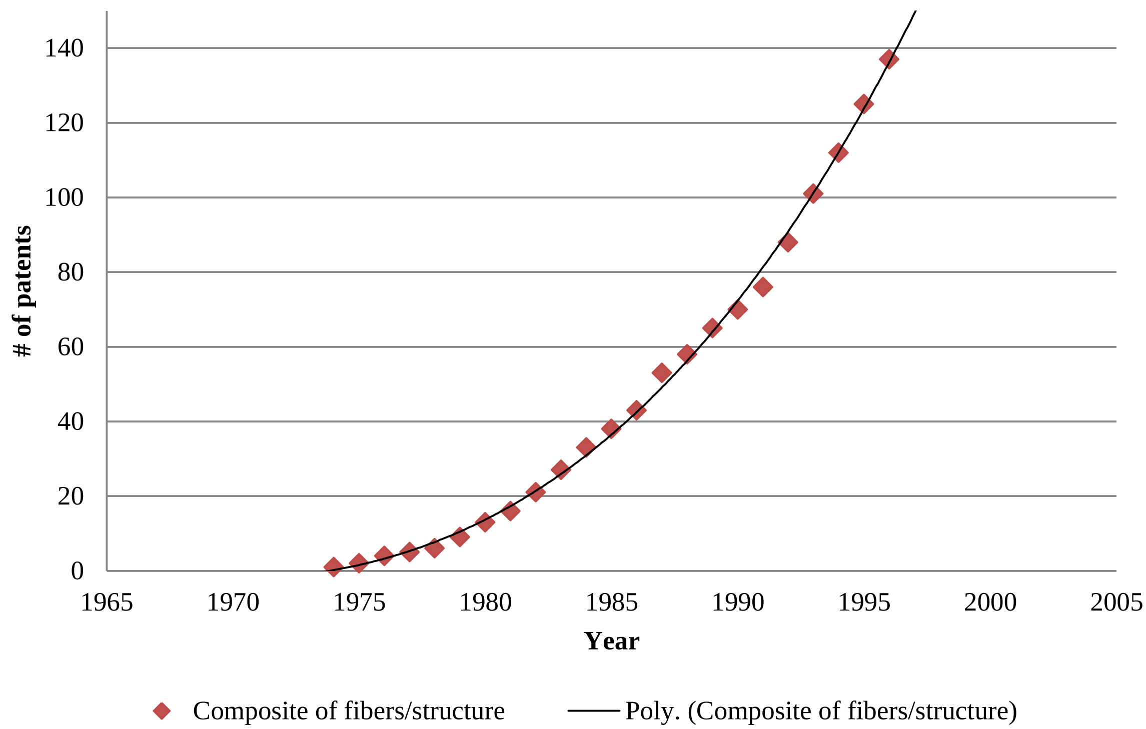

Figure 57. Composite of fibers/structure number of inventions data

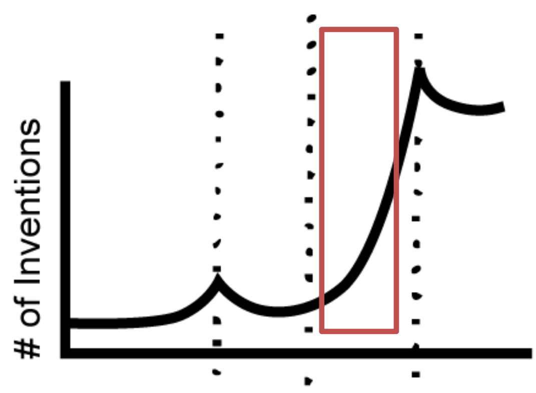

Figure 58. Composite of fibers/structure number of inventions s-curve

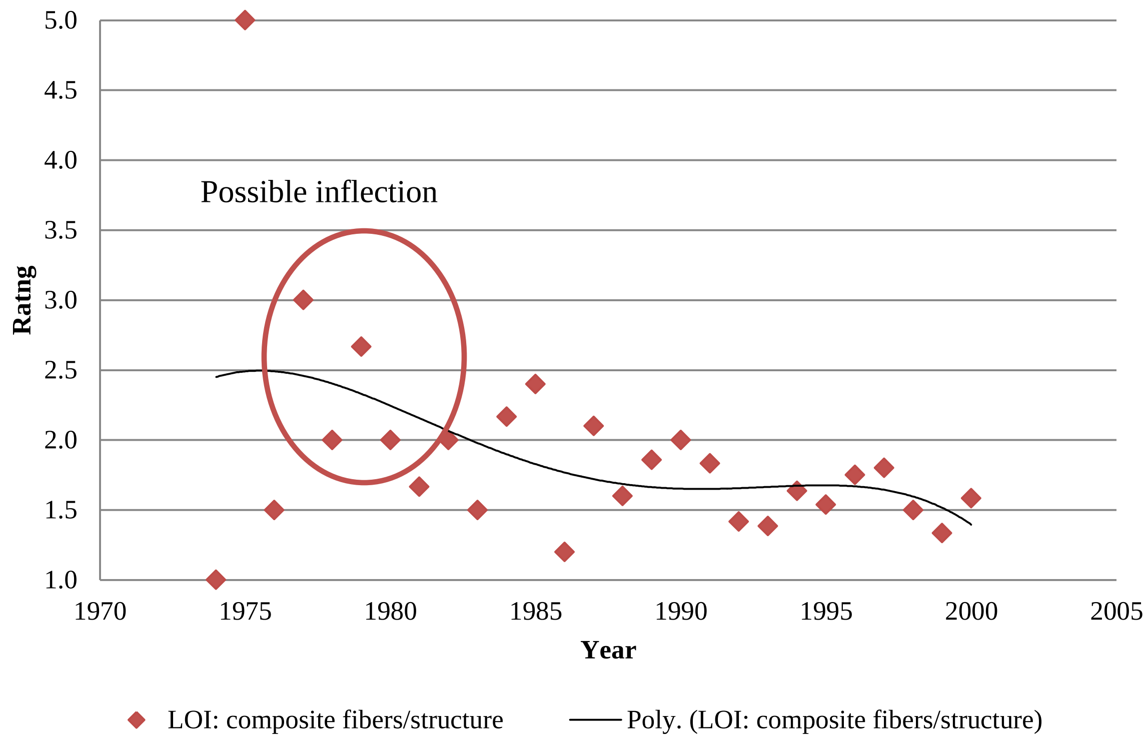

Figure 59. Composite of fibers/structure level of invention data

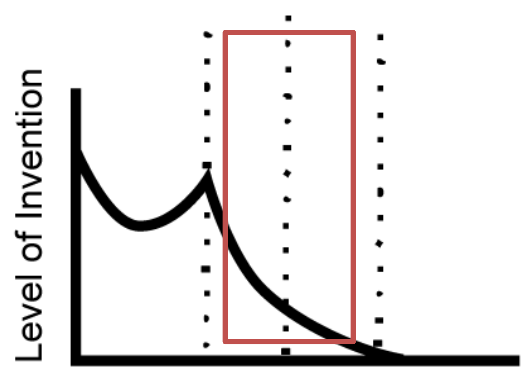

Figure 60. Composite of fibers/structure level of invention s-curve

web formation/bonding.

The web formation/bonding number of inventions data is shown in *Figure 61*. When compared to the descriptive s-curve in *Figure 62*, it is difficult to place the subsystem element in a single stage of development. The dataset appears to be in the portion of the graph highlighted by the green rectangle which included both the growth and maturity stages. The web formation/bonding LOI data results are shown in *Figure 59*. When the LOI data is compared to the LOI s-curve in *Figure 64*, the system element appears to be in the growth stage. Both descriptive s-curves were used to evaluate the maturity of web formation/bonding element and determined it's in the growth stage. Considering slowing number of patents in the area compared to other system elements this system element maybe constraining the overall system so there may be a need for new web formation/bonding technologies to help air filtration media move forward.

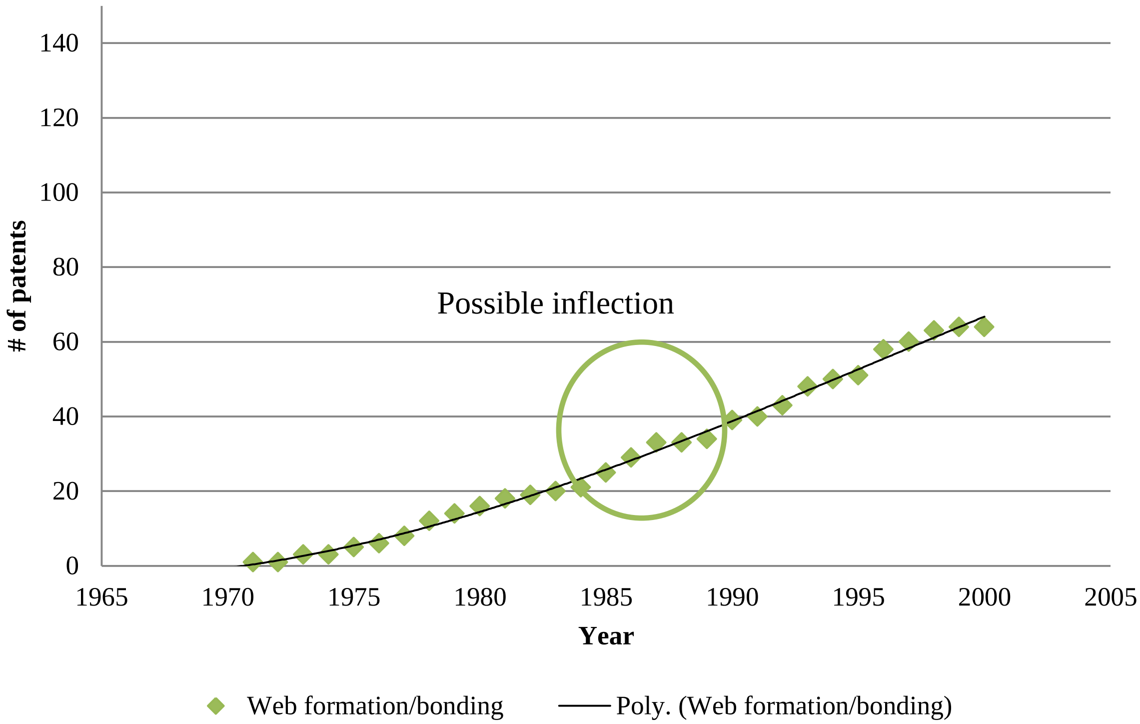

Figure 61. Web formation/bonding number of inventions data

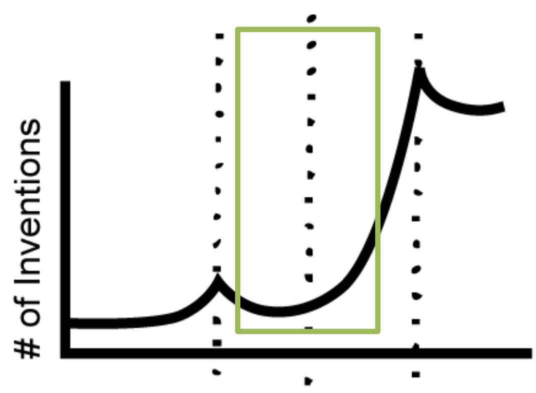

Figure 62. Web formation/bonding number of inventions s-curve

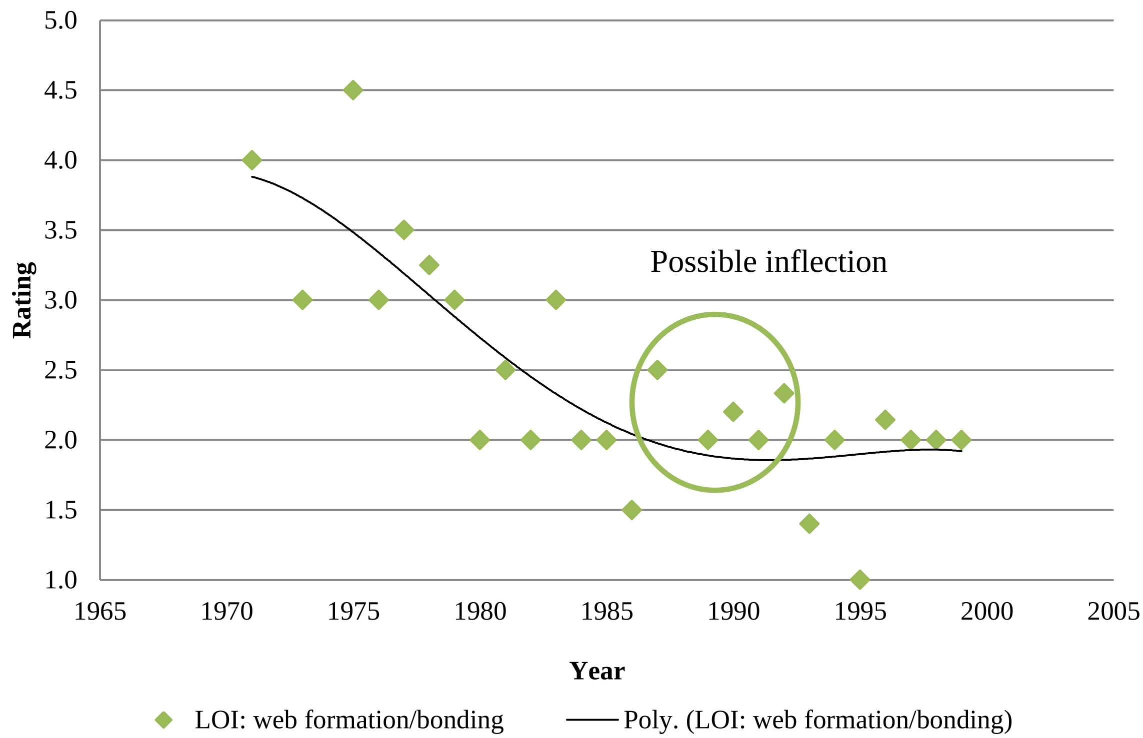

Figure 63. Web formation/bonding level of invention data

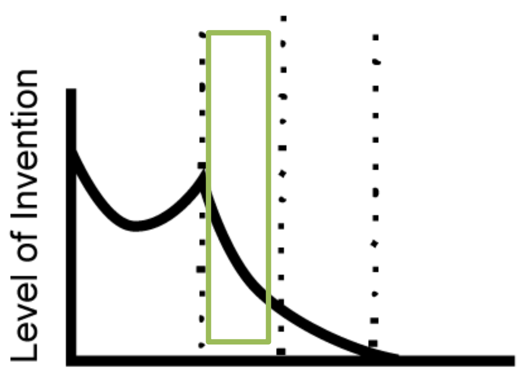

Figure 64. Web formation/bonding level of invention s-curve

finishing.

The finishing element number of inventions data is shown in *Figure 65*. When compared to the descriptive s-curve in *Figure 66*, it's difficult to place the subsystem element in a single stage of development. The dataset appears to be in the portion of the graph highlighted by the light blue rectangle which includes both the growth and maturity stages. The finishing LOI data results are shown in *Figure 67*. When the LOI data is compared to the LOI s-curve in *Figure 68*, the system element appears to be in the growth stage. Using both descriptive s-curves to evaluate the subsystem element for maturity it was determined finishing is in the growth stage. Considering the maturity, number of patents and rate of patenting in the area compared to other system elements this area should be observed for potential developments and opportunities for use in air filtration media.

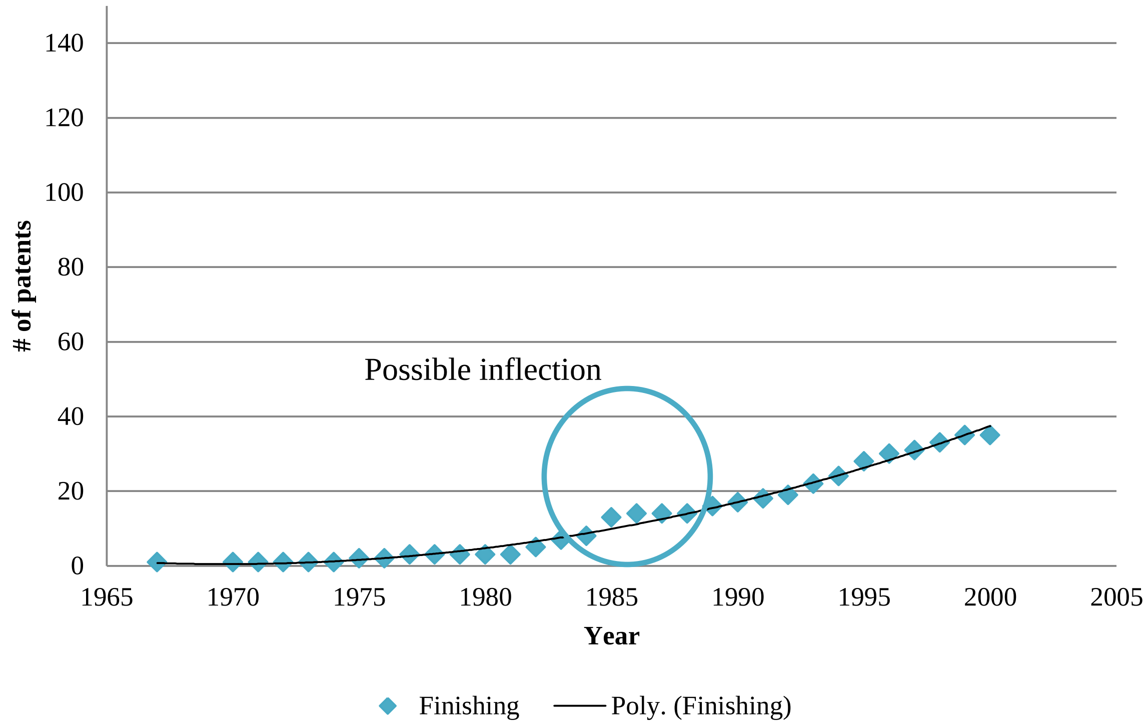

Figure 65. Finishing number of inventions data

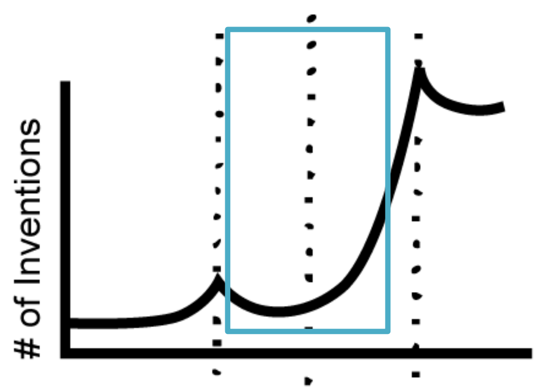

Figure 66. Finishing number of inventions s-curve

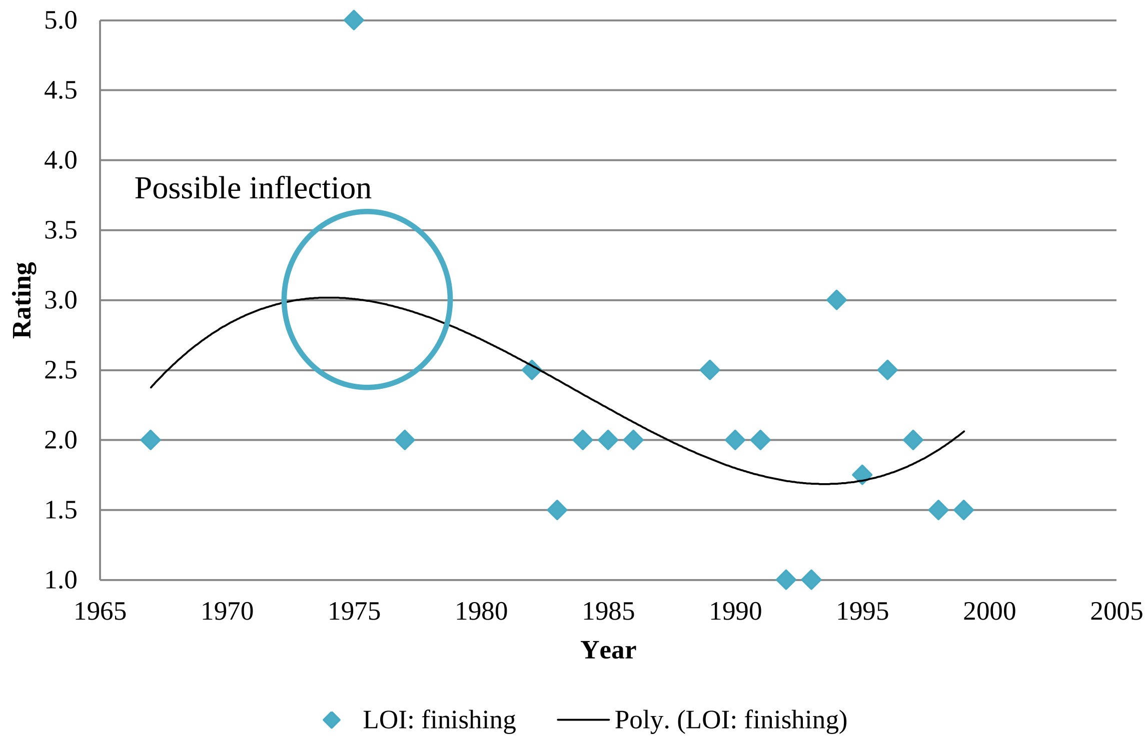

Figure 67. Finishing level of invention data

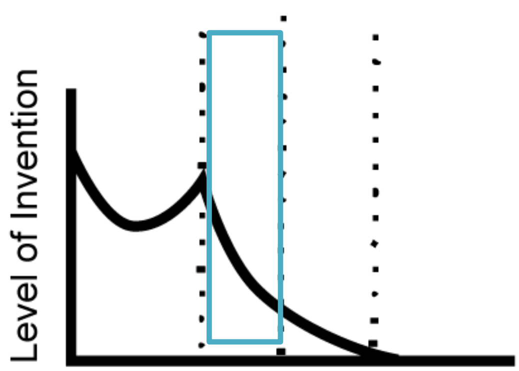

Figure 68. Finishing level of invention s-curve

filtration device.

The last system element reviewed was the filtration device. As previously mentioned this is actually the super-system for air filtration media. This element was included because many of the patents reviewed were categorized as a filtration device and the media is a component within the device. The filtration device number of inventions data is shown in *Figure 69*. When compared to the descriptive s-curve in *Figure 70*, there isn't an obvious inflection point but the dataset appears to be in the portion of the graph highlighted by the purple rectangle which includes the growth and maturity stages. The filtration device LOI data results are shown in *Figure 71*. When the LOI data is compared to the LOI s-curve in *Figure 72*, the system element appears to be in either the growth or maturity stage. Using both descriptive s-curves it was determined the filtration device element is in the early stages of maturity. The primary focus of the patent search was air filtration media so the data for the super-system, filtration device, isn't all encompassing. However, it appears from the total number of patents there has been significant development on the super-system when compared to most of the subsystem elements. It also appears that the super-system is maturing which could mean there is room for alternative technologies and research and development focus should be placed on the subsystem elements.

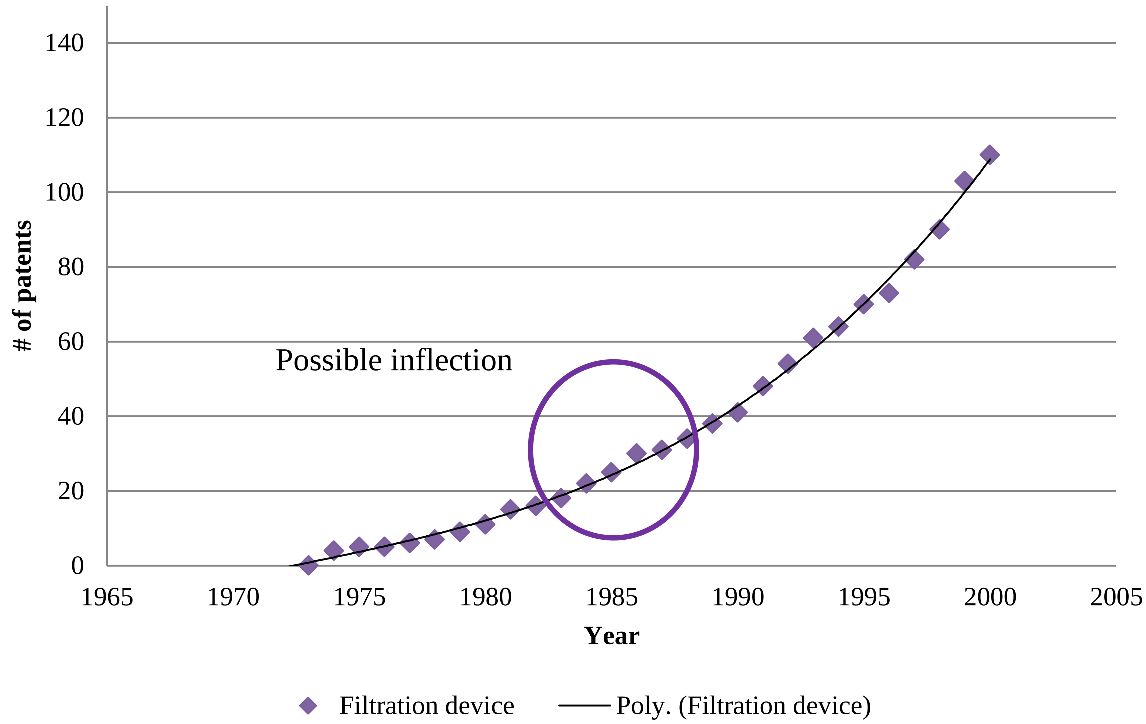

Figure 69. Filtration device number of inventions data

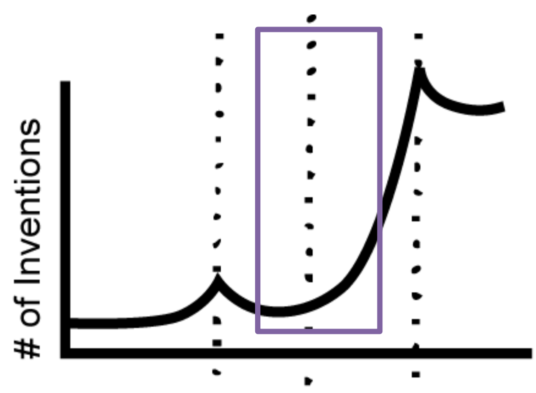

Figure 70. Filtration device number of inventions s-curve

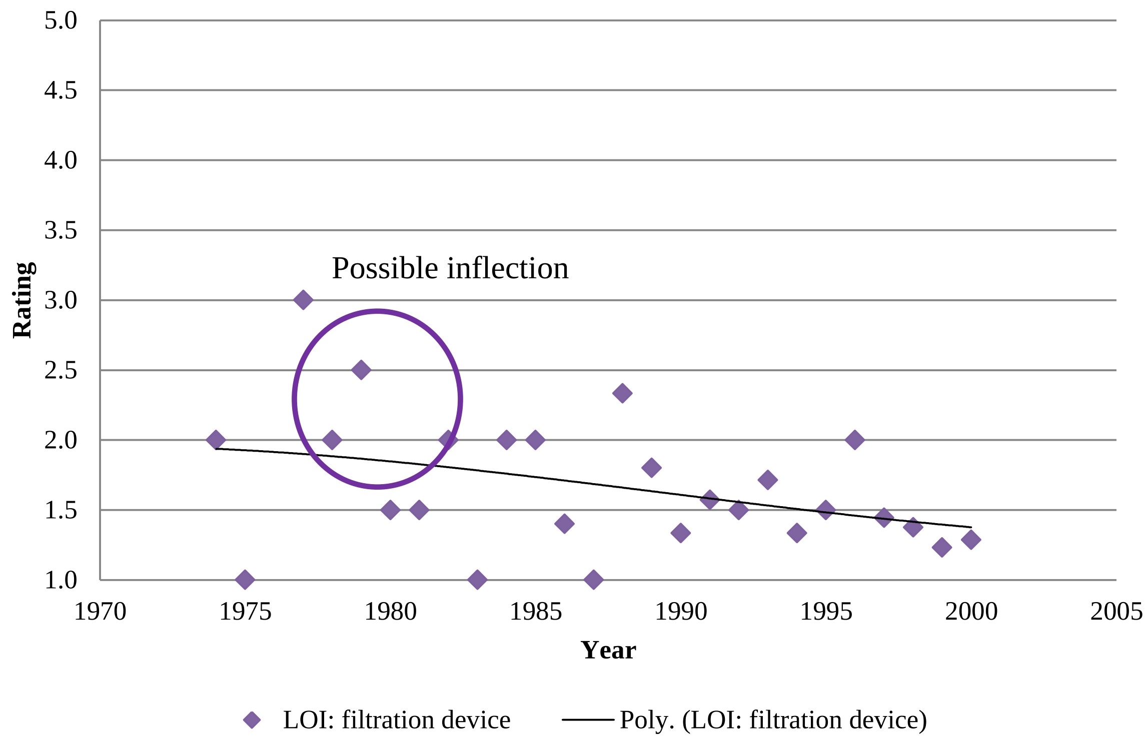

Figure 71. Filtration device level of invention data

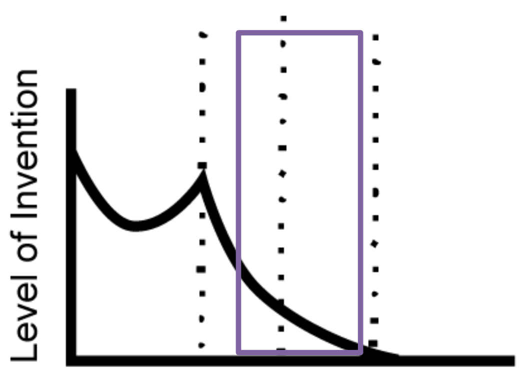

Figure 72. Filtration device level of invention s-curve

All of the system elements were reviewed and their maturity is illustrated in *Figure 73*. The composite fibers/structures element maybe reaching a limit and ultimately may be constraining the system. Composite fibers or structures are bi- or multi-component solutions, which are typically used when the technology doesn't exist to solve a problem with a simple mono-solution. To move air filtration media forward raw materials and web formation/bonding should be focused on to develop the next generation of fibers and structures. The data also shows opportunity for further development in the finishing element.

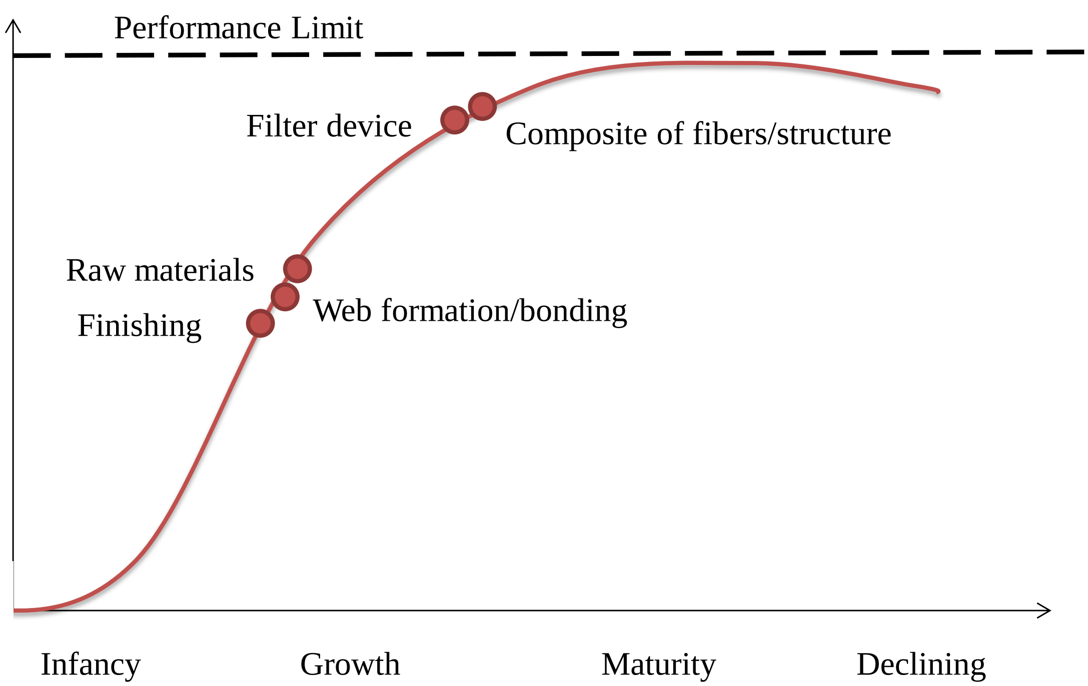

Figure 73. System elements maturity

Evolution towards increased ideality

Evolution towards ideality is based on the theory that all systems are made of both useful and harmful functions. Often a solution to one existing problem can cause additional harmful or unintended effects. The ideal state is when all the useful functions are performed without any harmful effects. As mentioned previously ideality could be considered a super-pattern and all other patterns are moving the system towards ideality. Ideality is often expressed in the form of a philosophical equation as shown in *Figure 74*. Although ideality can't be calculated, TRIZ practitioners often use the ideality equation to understand how far away the current state is from the ideal state. In *Table 29*, an ideality list for air filtration media was developed by the forecaster. The useful functions in bold are the most important for the system to serve its primary function which is to remove contaminates from an air stream. Based on the review of patents and forecaster's understanding of the state-of-the-art in air filtration media as of 2000 the radar chart in *Figure 75* was constructed to visualize ideality as of 2000. Using the ideality pattern to predict potential future paths, the areas of indication of contamination, self-cleaning and selective capture have the most opportunity for growth. The other useful function areas should also continue to see development.

$$\text{Ideality} = \frac{\text{All useful functions}}{\text{All harmful functions}}$$

Figure 74. Ideality equation

Table 29. Ideality list

Useful functions	Harmful functions
100% capture efficiency for all contaminants	Decreased capture efficiency
Pressure drop of 0	Increased pressure drop
Infinite contaminant holding capacity	Decreased contaminant holding capacity
Selective capture	Unable to selectively capture
Self-cleaning	Dirty filter requires replacement
	Dirty filter requires disposal
No energy consumption	Use of filter increases energy consumption
Infinitely small, takes up no space	Filter takes up space
Indication of when filter is contaminated	Unable to tell when filter is contaminated

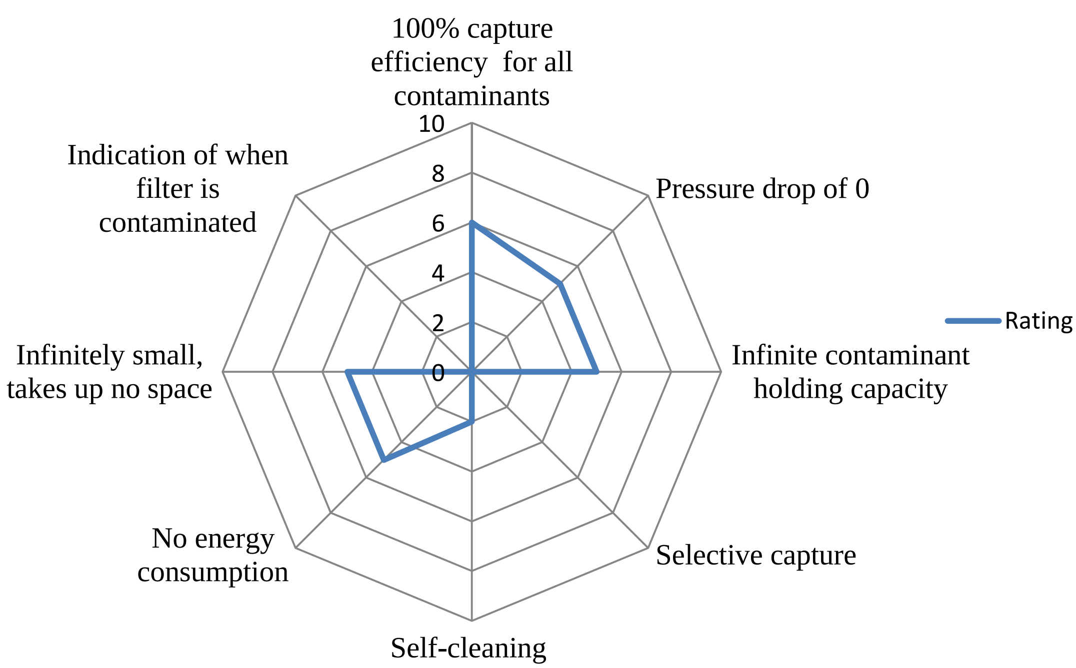

Figure 75. Radar chart for current state of ideality, 2000

evolution toward increased dynamism and controllability.

The evolution toward increased dynamism and controllability says the system continues to increase in functions, become more flexible and easier to control over time. The illustration in *Figure 76* shows the TRIZ stages of progression towards increased dynamicity. One of the primary functions of air filtration media is to capture contaminants. When considering dynamism the current air filter media uses 2 mechanisms for capturing contaminants, solid fixed media with various pore sizes that are designed to mechanically capture specific particle sizes and the field of electrostatic attraction. Both of these mechanisms are highlighted in green in *Figure 77* and the areas highlighted in yellow show stages that were skipped. Now thinking of an ideal filter media, this would be a more dynamic media capable of adapting itself to differing contaminant types so the filter had 100% capture efficiency for all contaminants. To move air filtration media towards this ideal state dynamism tells the developers to look at the stages that were skipped to determine if they could be applied to make the media more flexible and in this case a dynamic system that adapts to remove all contaminants. Another possible direction is use of additional fields other than electrostatic attraction. The complete list of fields is discussed later under the pattern of evolution toward micro-level and increased use of fields. Air filtration media's primary functions are to remove contaminants from the air and hold them and the systems are currently performing these functions. When looking at the ideality list there are several additional functions the system could perform including, selective capture, self-cleaning and an indication of filter contamination. *Figure 75* illustrates selective capture and indication of filter contamination have had no development but self-cleaning has received some attention.

Currently industrial bag house filters utilize a mechanical force to shake the filter so the particles fall and can be removed with suction; this is an automated process. The law of dynamicity says the function of self-cleaning will continue to become more flexible so developers should look to areas in dynamicity that were skipped or haven't been fully exhausted to identify where the technology will go next. The self-cleaning functions path towards dynamicity is illustrated in *Figure 78*.

Figure 76. Increasing dynamicity

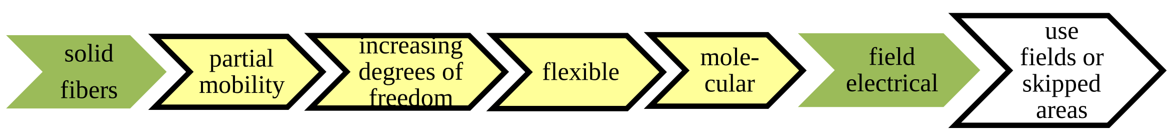

Figure 77. Increasing dynamicity of collection mechanisms in air filter media, 2000

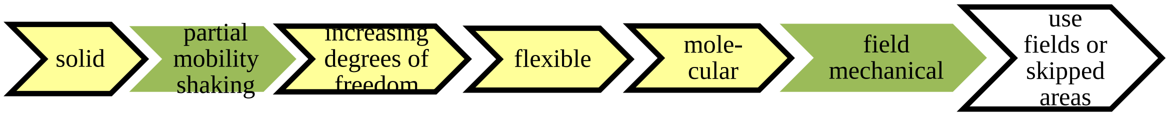

Figure 78. Increasing dynamicity of self-cleaning function, 2000

increased complexity then simplification.

The pattern of increased complexity then simplification says the addition of useful functions often make the system more complex but then are always moving towards a consolidated, simpler system or solution. An example of this pattern in air filtration media is moving from a traditional woven textile to a nonwoven. A woven fabric requires formation of yarns that are interlocked into a fabric structure using looms. A nonwoven fabric is formed directly from fibers in a single process. To move air filtration media towards ideality, a filter should be able to capture the maximum range of contaminates with a low pressure drop and have a high contaminate holding capacity. Filtration media was briefly developed using traditional textiles then nonwovens made-up of a single fiber type, primarily fiberglass. To capture a wider range of particle sizes in a single filter a solution observed in the patent literature was the use of composites in the form of fiber blends of different sizes or combining multiple nonwoven fabrics together in the form of composites. These were often referred to as gradient filters in the patent literature and aimed at capturing both large and small particles with a lower pressure drop. This move from a single fiber to composites fibers/structures using multiple manufacturing steps is an example of increased complexity. The pattern of increased complexity then simplification predicts that air filtration media will eventually move to a simpler system as illustrated in *Figure 79*.

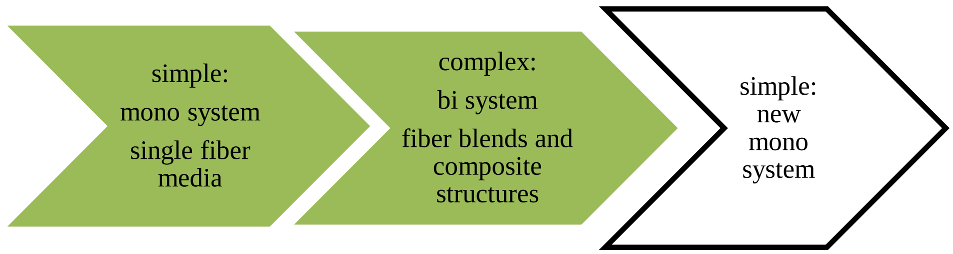

Figure 79. Increased complexity then simplification

evolution with matching and mismatching components.

The evolution with matching and mismatching components says that changing how system components are paired or work together can help minimize harmful functions. The elements can be unmatched, matched, mismatched or dynamic matching and mismatching. There wasn't a specific application identified for this pattern within air filtration media but this pattern can be seen in air filtration devices through the use of pre-filters for HEPA filters. HEPA filters are designed to capture 0.3 µm particles with 99.97% collection efficiency. If HEPA filters are exposed to larger particles the filter will clog quickly, so a custom filtration system is typically developed that includes a series of pre-filters that are designed to remove the larger particles. The HEPA captures the fine particles and the life of the filter is extended. The use of pre-filter and HEPA filter is an example of mismatched elements to solve the clogging and capture efficiency problems. The current state for air filter devices is illustrated in *Figure 80*. The pattern of matching and mismatching components would have air filter developers look at the untapped areas for future solutions to these problems.

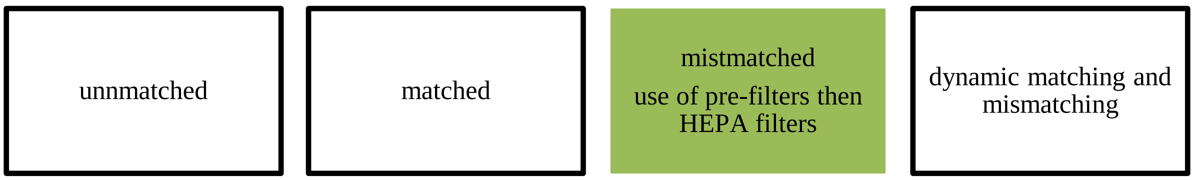

Figure 80. Evolution with matching and mismatching components for air filter device, 2000

evolution toward micro-level and increased use of fields.

The pattern of evolution toward micro-level and increased use of fields says systems move from macro systems to micro systems to the use of fields. An updated description might also include nano systems after micro systems. There is also a hierarchy of fields associated with this pattern as shown in *Figure 81*. The fields highlighted in green indicate fields used by air filtration media, the yellow indicates fields that were skipped and the white indicate fields that haven't been used. This pattern can be seen in air filtration media with the move from macro-sized fiberglass, to microglass, to the use of synthetic microfibers, to the use of electrostatic charging and as of 2000 there was some development around sub-micron fibers. The progression for air filtration media is illustrated in *Figure 82*. As of 2000 air filtration media was focused on the use of the mechanical field by going to smaller fiber sizes and the use of electrical fields to attract particles. The use of electrostatics in air filtration allows the filter to capture smaller particles while having an open structure which decreases the pressure drop. There are some harmful functions associated with both smaller fibers and electrostatic charging. When using smaller fibers the pressure drop can increase and electrostatic charge isn't permanent so there is some hesitation in the industry to use electrostatically charged filters for specialized applications like HEPA filtration. The law of evolution towards micro-level and increased use of fields predicts that air filtration media will continue to move towards smaller fibers, the use of electrostatic charging will continue and there are many fields that haven't been explored. Research and developers should look to the fields that have been skipped or not applied to identify future directions for improving air filtration media.

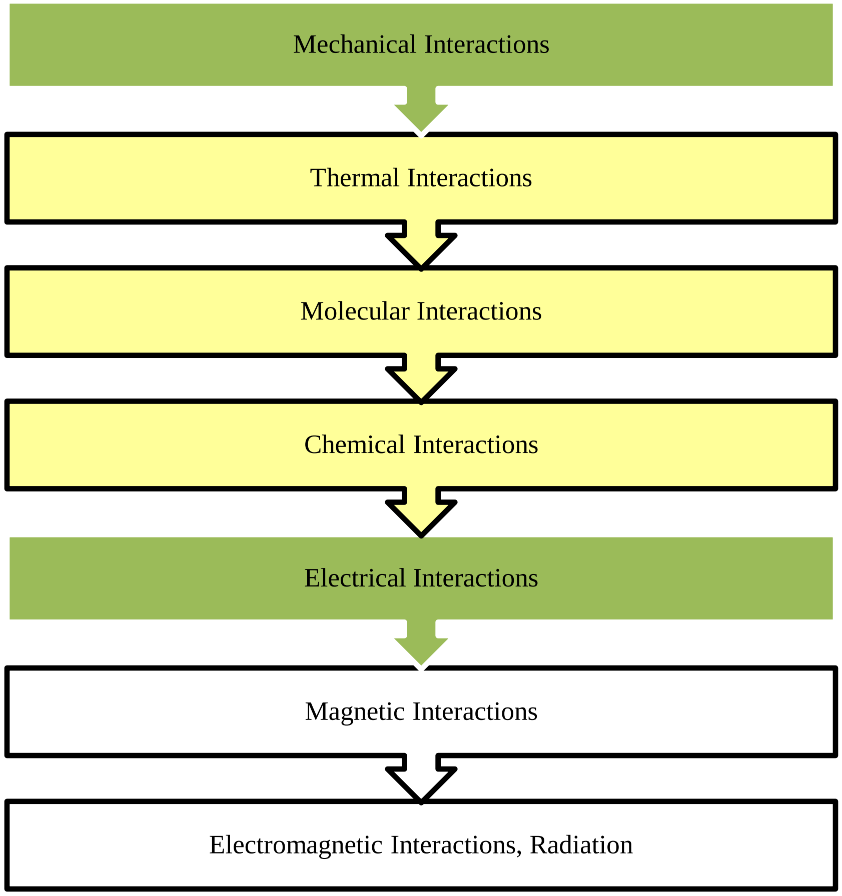

Figure 81. Hierarchy of fields

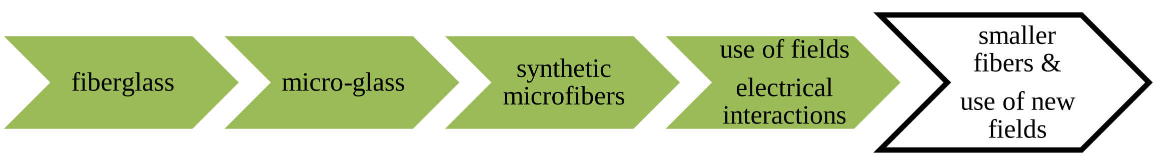

Figure 82. Air filtration media evolution towards micro-level and increased use of fields, 2000

evolution toward decreased human involvement.

The pattern of evolution towards decreased human involvement is easy to understand when thinking of manufacturing and the automation of devices. In air filtration media the major areas for human involvement are in the installation, removal and disposal of the air filters. When considering the ideality goals, the useful function that would decrease human involvement is self-cleaning. If a filter could capture contaminates and self-clean, the life of the filter would be infinite and human wouldn't need to remove or dispose of them. Again, this is an area that has seen very little development but should be pursued.

TRIZ TF for air filtration media

In the following section the findings from the TRIZ TF are summarized and future directions for air filtration media are discussed.

- Technology maturity mapping
    - Air filtration media is in the beginning stage of maturity
    - LOI ratings indicate a breakthrough technology hasn't been developed as of 2000
    - R&D should be on the lookout for the next breakthrough invention(s) over the next 5-10 years
- Non-uniform development of system elements
    - Raw material is in the growth stage. Considering the maturity and the limited number of patents in the area compared to other system elements there is opportunity for new technology development in the area of raw materials.

- Composite fibers/structures are in the maturity stage. Considering the maturity and the large number of patents in the area compared to other system elements, this system element may be reaching a limit and one of the other elements should be further developed to help air filtration media move forward.
- Web formation/bonding is in the growth stage. Considering slowing number of patents in the area compared to other system elements this system element maybe constraining the overall system so there may be a need for new web formation/bonding technologies to help air filtration media move forward.
- Finishing is in the growth stage. Considering the maturity, number of patents and rate of patenting in the area compared to other system elements this area should be observed for potential developments and opportunities for use in air filtration media.
- Filtration device super-system is in the maturity. The primary focus of the patent search was air filtration media so the data for the super-system, filtration device, isn't all encompassing. However, it appears from the total number of patents there has been significant development on the super-system when compared to most of the subsystem elements.

- Ideality
    - The ideality pattern predicts the areas of indication of contamination, self-cleaning and selective capture have the most opportunity for growth. The other useful functions including 100% capture efficiency for all contaminants, pressure

drop of 0, infinite contaminant holding capacity, no energy consumption, infinitely small and takes up no space should also continue to see development.

- Evolution towards increased dynamism and controllability
    - The ideal filter media would be a more dynamic media capable of adapting itself to differing contaminant types so the filter had 100% capture efficiency for all contaminants. To move air filtration media towards this ideal state dynamism tells the developers to look at the dynamism steps that were skipped or not fully exhausted to determine if they could be applied to make the media more flexible.
    - When looking at the ideality list there are several additional functions the system could perform including, selective capture, self-cleaning and and indication of filter contamination.
    - Currently industrial bag house filters utilize a mechanical force to shake the filter so the particles fall and can be removed with suction; this is an automated process. The law of dynamicity says the function of self-cleaning will continue to become more flexible so developers should look to areas in dynamicity that were skipped or haven't been fully exhausted to identify where the technology will go next.
- Increased complexity then simplification
    - To capture a wider range of particle sizes in a single filter a solution observed in the patent literature was the use of composites in the form of fiber blends of different sizes or combining multiple nonwoven fabrics together in the form

of composites. These solutions were aimed at capturing both large and small particles with a lower pressure drop. This move from a single fiber to composites fibers/structures using multiple manufacturing steps is an example of increased complexity. The pattern of increased complexity then simplification predicts that air filtration media will eventually move to a simpler system.

- Evolution with matching and mismatching components
  - The use of pre-filter and HEPA filter is an example of mismatched elements to solve the clogging and capture efficiency problems. The pattern of matching and mismatching components would have air filter developers look at the untapped areas of unmatched, matched and dynamic matching and mismatching for future solutions to these problems.
- Evolution toward micro-level and increased use of fields
  - The law of evolution towards micro-level and increased use of fields predicts that air filtration media will continue to move towards smaller fibers, the use of electrostatic charging will continue and there are many fields that haven't been explored. Research and developers should look to the fields that have been skipped or not applied to identify future directions for improving air filtration media.
- Evolution toward decreased human involvement
  - When considering the ideality goals, the useful function that would decrease human involvement is self-cleaning. If a filter could capture contaminates and

self-clean, the life of the filter would be infinite and human wouldn’t need to remove or dispose of them. There has been little to no development so this functionality isn’t a short- or mid-term prediction.

CHAPTER 5: Evaluation of Individual and Hybrid Forecasts

The tech mining and TRIZ TF methodologies have been thoroughly documented in the previous chapters. The hybrid tech mining, TRIZ TF forecast is the combination of the results from both methodologies. In the following section all three methods and forecasts are compared and evaluated based on ease of use, time, value of information and accuracy.

Evaluation of ease of use

tech mining.

Tech mining offers the ability to utilize the large amount of available structured and unstructured text data for use in monitoring and forecasting of technologies. Collection of data is often a major challenge in research design so the use of bibliographic databases is one of tech mining's biggest strengths due to widespread use of these databases at universities and many companies. Although tech mining maybe performed without using specialized text mining software, the results of tech mining TF would be very limited without it. The basic analysis and concepts of tech mining are easily implemented although expert opinions may differ on the theory behind the analysis. The advanced analysis and trend extrapolation require the forecaster to have a deeper understanding of the theory so relationships and inferences can be made that aren't obvious within the data. Ultimately, tech mining is relatively easy to use for high level descriptive analysis of a dataset but to truly make predictions from the data can be challenging.

TRIZ TF.

TRIZ TF was the most challenging initially to structure the approach and determine how to implement the technique due to the limited and vague descriptions in the literature.

After a clear approach was defined, implementation of both the analysis of the technological system and technology maturity mapping weren't difficult to implement. The resources required to implement these two steps was easily accessible although one of the descriptive s-curves wasn't addressed. The biggest challenge within the TRIZ TF was the application of the patterns of evolution. The TRIZ algorithm was initially designed as an approach to solving engineering problems and has since been loosely adopted for technology forecasting. Identifying which and how the patterns should be applied is a subjective process which makes repeatability difficult. The approach taken in this research study was to use the pattern of ideality as a super-pattern and apply the other patterns of evolution to move the technology towards ideality. Overall the two most common steps seen in the literature, analysis of technological system and technology maturity mapping, were relatively easy to implement while applying the patterns of evolution provided some challenges.

hybrid tech mining, TRIZ TF.

Combining the two forecasts brings with it the strengths and weaknesses of both in terms of ease of use. There were some potential benefits to ease of use from combining the techniques. The same patent dataset was used for both forecasts and the same software used to conduct the tech mining analysis was used to track the level of invention and type of invention classifications for the TRIZ TF. Another potential benefit would be to conduct the analysis of the technological system prior to starting the tech mining process because this would provide some additional insight for the forecaster into the terminology and technologies. The same challenges with extracting meaningful predictions from the individual forecasts still holds true for the hybrid forecast.

Evaluation of time

This research was conducted over an extended period of time and the timing for each forecasting methodology wasn't directly tracked; therefore, the following assessment of time is a qualitative assessment made by the forecaster. The coverage of this topic is included to provide additional information to the reader.

tech mining.

Tech mining does allow the analysis of a large amount of data in a shorter amount of time then otherwise possible. A large amount of the forecasting time was spent in planning and collection of the data. This included designing and implementing the searches. The total number of records for export limitations of the various databases made the collection of the records tedious. If the forecaster was using an extremely large dataset, this portion of the method could be unreasonable and the forecaster may need a different level of access to the databases. Depending on the software package used, the cleaning of the data could be extremely time consuming. Vantage Point included several standard list cleanup options and thesauri that could be used and modified which made the cleaning process simpler. The most challenging data cleaning was any cleaning related to words or phrases. Although these weren't heavily addressed in this research, removal of common words and creation of useful thesauri is time consuming. Once the data is imported and cleaned, the forecaster is able to view and analyze the dataset in a variety of ways. The amount of time required to conduct most of the analysis techniques are comparable with other analytical techniques typically used in academic research. There was a significant amount of spent going through the available data to determine what was useful and valuable to the forecast. The amount of time spent making decisions about how to analyze the data would of course decrease as the experience of the forecaster increased but there is the potential for getting stuck in the data. Depending on the size of the dataset and level of analysis required tech mining can be a relatively quick process or require a significant amount of time.

TRIZ TF.

Unlike tech mining, TRIZ TF requires the forecaster to actually review and evaluate individual patents. This portion of the process is where a majority of the time was spent. In order to make this a reasonable goal approximately 10% of the patents were reviewed and the TRIZ TF was based on these 364 patents as opposed to the total dataset. The evaluation for level of invention and classification by type of invention required the forecaster to access, read and classify each patent. The amount of time it takes to review and evaluate the patents will vary depending on the forecaster and the familiarity with the topic being forecasted. Some of the patents were more challenging to review then others and the exact evaluation time was not recorded. To provide some perspective on timing, if it took a forecaster on average 20 minutes per patent it would take approximately 121 hours to review 364 patents. In terms of timing the remaining tasks involved in TRIZ TF are comparable with other analytical techniques typically used in academic research.

hybrid tech mining, TRIZ TF.

Combing the two forecasting methods obviously increases the amount of time required to conduct the forecast. The TRIZ TF process of evaluating patents for the technology maturity mapping contributes the largest amount of time for a single task.

Evaluation of value of information

The value of information was assessed by the ability of each method to address the forecasting questions developed for the study. In *Table 30* each forecast is labeled as Yes (Y), No (N), or Limited (L) depending on the ability to address each forecasting question. Each forecast is then discussed in more detail in the following sections.

Table 30. TF methods ability to address forecasting questions

Forecasting Question	tech mining	TRIZ TF	Hybrid
Assess the maturity of current technologies and trends.	Y	L	Y
What current technologies or trends merit ongoing attention?	Y	L	Y
What emerging technologies or trends merit ongoing attention?	L	L	L
What are the component technologies that contribute importantly?	N	Y	Y
What is driving this technology development?	Y	L	Y
What are the likely development pathways for this technology?	L	Y	Y
Who are the available experts?	Y	N	Y

tech mining.

During the design and development of the tech mining forecast several strengths were recognized. The first is the ability to identify who is working in an area. Tech mining can easily be used to identify leading authors, sources, organizations, countries, inventors, patent assignees, etc. Although it was outside of the scope of this research tech mining was observed to be a good tool for competitive intelligence gathering and digging into the data to identify what specific groups are researching and patenting. Another tech mining strength is the ability to track technologies and trends over time which makes tech mining useful for assessing maturity and rate of change on a topic. The maturity and rate of change are good indicators to use to identify which technology or trends are receiving lots of focus and therefore merit attention. Tech mining is also a good tool to identify what is driving a technology area by tracking where the most research is being conducted. In the case of the air filtration media forecast, industry was leading the development while basic and applied research lagged behind. There were some indicators that this pattern may be beginning to change. Since tech mining forecasting is largely based on the amount and quality of information that can be extracted from bibliographic databases, there are some limitations in the area of emerging technologies and trends. Identifying which emerging technologies merit the most attention is challenging for any forecasting method because the nature of emerging technologies and trends is there is little known about them. The use of tech mining software does offer the ability to quickly search through these emerging areas and make observations about what, if anything is being covered in each stage of development. Another limitation for tech mining is the ability to forecast likely future pathways. This is described as limited because tech mining can only forecast development pathways for technologies and trends that received good coverage in bibliographic databases and these technologies and trends must be known to the forecaster. Tech mining uses trend analysis to predict the future pathways of known technologies and trends. Tech mining doesn't predict new directions like

TRIZ TF. The only forecasting question that tech mining wasn't able to answer was, "what are the component technologies that are important contributors to the technology system?"

TRIZ TF.

During the development of the TRIZ TF several strengths were identified. The first was the in-depth knowledge of the technology and innovations gained through the analysis of the technological system and maturity mapping steps. These steps help the forecaster understand where the technology currently is, which gives the forecaster better insight into where the technology might go. The patterns of evolution provide the forecaster with a structured approach to forecasting development pathways for the technology. The TRIZ TF goes beyond typical forecasting methods by making longer term predictions and looking at the technology from the perspective of ideality. Although this is TRIZ TF's biggest strength, the challenge is to attach a timeframe to these predictions. TRIZ TF has limited ability to assess the maturity of both current and emerging technologies and trends. The term limited is used because the maturity mapping is primarily focused on a single technology and requires maturity mapping of each technology and trend separately. The TRIZ TF is also limited in determining what is driving a technology area because although maturity mapping uses multiple s-curves as indicators of maturity the process doesn't highlight which areas are driving the technology forward. The analysis of the technology system components and maturity mapping of these components provides significant insight into which technologies are contributing to the system and has received the most development. One area that TRIZ TF doesn't address is the identification of experts.

hybrid tech mining, TRIZ TF.

As illustrated in *Table 30* the combination method offers better coverage of the forecasting questions identified for this study then either single method. The question of identifying which emerging technologies or trends merit the most attention is still limited but this is a challenge for any forecasting method. The table shows that tech mining is able to fully address more of the forecasting questions then TRIZ TF but the addition of TRIZ TF gives the hybrid forecast the ability to also understand component technologies and predict likely new pathways.

Comparison of accuracy

Each forecast resulted in a report that included a series of predictions based on the information provided by the forecast method. The tech mining forecasts were categorized as short term, 5 years, or long term 10 years but the TRIZ TF forecast weren't associated with a time frame. The predictions were evaluated for accuracy using a modified version of the classification approach developed by Wise (1976). Each prediction was classified as fulfilled, in progress or not proven. The predictions were classified as fulfilled, in progress or not proven using evidence found in scholarly or industrial literature and patents data.

tech mining.

The results for tech mining evaluation were positive and can be found in *Table 31*, *Table 32* and *Table 33*. The existing technologies and trends forecasts results for tech mining were mostly classified as fulfilled. The spunbond prediction was not able to be validated and although spunbond is being used in multiple air filtration applications one primary use is as a supporting substrate for meltblown filter media. The one inaccurate prediction was the increased use of membranes. Membranes are still an important filtration technology and often discussed in industry literature for their superior performance but this has not transferred into a significant market share. The market share of membranes used in air filtration media isn't reported separately and usually grouped with others at 1-5%. Due to the lack of data there was only one forecast statement made for the emerging technologies and that was related to increased importance of antimicrobial functionality in air filters. This was found to be a true statement. Although no forecast prediction was made regarding the use of nanofibers, the tech mining forecast did identify electrospinning as a potential technology for making nanofibers which turned out to be an important nanofiber technology.

Table 31. Tech mining existing technology evaluation of forecast for accuracy

Technology	Forecast 2005	Evaluation	Forecast 2010	Evaluation
Glass fiber microglass	low growth but remain leading technology in air filtration market	**Fulfilled** (INDA, 2008, pp. 77-80)	low growth but slowing compared to previous years	**Fulfilled (INDA, 2011, p. 36)** Being replaced with MB and composites
Wetlaid	low growth and no new developments in technology but continued use for glass fibers	**Fulfilled** (INDA, 2008, pp. 28 & 77-80) 4 patents (*Table 52*)	low growth and no new developments in technology but continued use for glass fibers	**Fulfilled** (INDA, 2011, p. 36) 9 patents (*Table 52*)
Spunbond	moderate growth and increased market share in air filtration market	**Fulfilled** (INDA, 2008, pp. 77-80)	moderate growth and increased market share in air filtration market	**Not proven** Used as a support substrate for MB media
Meltblown	moderate growth and increased market share in air filtration market	**Fulfilled** (INDA, 2008, pp. 28 & 77-80)	moderate growth and increased market share in air filtration market	**Fulfilled** (INDA, 2011, p. 36)
Needlepunch	low growth and but continued use in air filtration media	**Fulfilled** (INDA, 2008, pp. 28 & 77-80)	low growth and but continued use in air filtration media	**Fulfilled** (INDA, 2011, p. 36)
Split film/fiber	low growth but continued use in air filtration media	**Fulfilled** (Duran, 2004) 13 patents (*Table 53)*	low growth and but continued use in air filtration media	**Fulfilled** 5 patents (*Table 52*)
Membranes	moderate growth and increased market share in air filtration market	**Not proven** Lower growth (INDA, 2008, pp. 42 & 77-80)	moderate growth and increased market share in air filtration market	**Not proven** Lower growth , only makes up approximately 2-5% of total market

Table 32. Tech mining existing trends forecast evaluation of forecast for accuracy

Trend	Forecast 2005	Evaluation	Forecast 2010	Evaluation
Electret or electrostatics	moderate growth and increased market share	**Fulfilled** (INDA, 2008, p. 23)	moderate growth	**Fulfilled** (INDA, 2011, p. 36) MB media is charged
Composites	low to moderate growth	**Fulfilled** (INDA, 2008, pp. 16-18, 42, 66-74)	low to moderate growth	**Fulfilled** (Smith, Johnson & Associates, 2010)
HEPA filtration activity	moderate growth and increased market size	**Fulfilled** (INDA, 2008, pp. 3 & 38-40)	moderate growth and increased market size	**Fulfilled** (INDA, 2011, p. 36)

Table 33. Tech mining emerging technologies and trends evaluation of forecast for accuracy

Technology or trend	Observations	Evaluation
Introduction of nanofiber/submicron fibers	Due to the limited references to nanofibers or submicron fibers in the publications and patents related to air filtration, there isn't evidence as of 2000 to show how viable nanofiber technologies will be for air filtration in the 2005 or 2010. The one WOS article discusses the use of electrospinning for formation of nanofibers in air filters. The patents referred to the fibers as submicron fibers instead of nanofibers.	Electrospinning emerged as an important nanofiber technology (Smith, Johnson & Associates, 2010; Ward, 2005)
Antimicrobial functionality	All of the WOS, EV and DII records describe using antimicrobial treatments for air filters. Based on the increase of patents on the topic antimicrobial functionality is a growing area for air filtration.	**Fulfilled** (INDA, 2008, p. 3 & 51)

TRIZ TF.

The TRIZ TF results didn't have a time period associated with the predictions and were focused on the direction the overall technology system was headed. The results were mostly positive and are shown in *Table 34*. A majority of the predictions were classified as in progress because the technology will continue to evolve according to the prediction. The prediction of moving towards smaller and smaller fibers was fulfilled by the introduction and use of nanofiber technology. The predictions of moving toward 100% capture efficiency, pressure drop of 0, infinite contaminant holding capacity and no energy consumption were grouped together because these areas are interrelated performance properties and often discussed together in academic and industry literature. There were two predictions that couldn't be proven. The first was the development of an adaptive filter for particle capture and there wasn't any evidence in the literature or patents that this functionality had been developed. The prediction of use of other fields for capture mechanisms was also unproven but there were several patents found for water and biofiltration using the chemical and molecular interactions for capture so these would be areas to watch moving forward.

hybrid tech mining, TRIZ TF.

When combining the tech mining forecast results with the TRIZ TF results the forecaster gains information about future directions for known technologies and trends and predictions for new technology developents that otherwise wouldn't be identified. Each forecast resulted in more accurate predictions then un-proven predictions but the information gained from each forecast varied significantly. The tech mining provided more detailed forecasts for each technology and trend while the TRIZ TF provided a general direction for technology development. The value in combing tech mining and TRIZ TF lies in the different type of information provided by each forecast.

Table 34. TRIZ TF evaluation of forecast for accuracy

TRIZ TF statement	Evaluation
Indication of contamination	**In progress** EP 1728545: color change; JP 2000197805: color change; JP 2002361015: color change
Self-cleaning	**In progress** CN 1944722: use of additives; JP 2000317312: use of photocatalytic reaction; US 2010263541: use of water spray system; WO 2003037389: use of UV light; WO 2008110623: use of water spray system
Selective capture	**In progress** WO 200156678: use of fiber whiskers on surface
Adaptive filter for particle capture	**Not proven**
Move to a simpler system	**In progress** in the form of hybrid technologies WO 2009085679: combination of sub-micron and microfibers in single technology; US 2008315454: combining staple fibers and meltblown process into single technology
Move towards smaller fibers	**Fulfilled** (Ward, 2005; Sutherland, 2011)
Use of fields as capture mechanisms	**Not proven for air filtration** Patent application US 2012200229176: use of ion exchange in water; WO 2012068442: use of ligands in bio filtration
Move towards • 100% capture efficiency • Pressure drop of 0 • Infinite contaminant holding capacity • No energy consumption	**In progress** (Donaldson Filtration Solutions, 2010) (Homonoff & Burkhead, 2007; Sutherland, 2009)
Infinitely small, takes up no space	**In progress** (Macrofalt, 2003; Donaldson Company, 2004)

CHAPTER 6: Summary and Findings

Technology Forecasting has commonality with the broader field of Forecasting but also faces unique challenges. When developing a forecast for an existing technology TF is able to utilize historical data, but often a technology forecast is attempting to predict when and what will be the next technology innovation. Forecasting breakthrough technologies is challenging because they often disrupt previous trends and when in the concept stage limited to no data is available to develop the forecast. TF is not an exact science but with or without formal forecasts organizations are making decisions everyday based on their vision of the future. TF provides a systematic approach to looking at the possible futures and provides decision makers with information that helps them anticipate, drive and plan for the technology change that leads to breakthrough technologies and products. Technology forecasting techniques are often used in combination with the assumption the combined forecast will provide better results. It was hypothesized that strategically selecting and combining tech mining and TRIZ TF may offer improvements over either individual forecast. Tech mining utilizes the large volumes of digital information available to recognize possible development trends while TRIZ TF goes a step beyond traditional methods by extending into idea generation and providing a long term vision of the future.

The objectives of this research were to identify the type of information found in tech mining and TRIZ TF forecasts and determine if combining tech mining and TRIZ TF forecast results offers improvements over either single method. The research objectives were as follows:

Research Objective 1: To develop a methodology for a hybrid technology forecast through the combination of tech mining and TRIZ TF techniques.

Research Objective 2: To identify the type of information obtained from each individual forecasting method and the hybrid TF forecast.

Research Objective 3: To assess the hybrid tech mining, TRIZ TF forecast.

a. Determine if the combined forecast offers improvements over either single method.

Research Objective 1 was completed during the preliminary research in Phase 1 and the results can be found in Appendix A. Research Objectives 2 and 3 were completed during Phase 2 of the research study. In Phase 2 technology forecasts were conducted for a historical time period using tech mining and TRIZ TF methodologies. The tech mining, TRIZ TF and hybrid forecasts were described in detail and the results were evaluated for ease of use, time, value of information and accuracy. A summary of the findings from Research Objectives 2 and 3 are listed in the following sections, key findings and additional findings.

Key Findings

- Tech mining offers the ability to utilize and evaluate large amounts of data and is relatively easy to use for high level descriptive analysis and forecasting predictions are based primarily on trend extrapolation.
- TRIZ TF steps of analysis of the technological system and technology maturity mapping were easy to implement while applying the patterns of evolution provided some challenges.

- Combing tech mining and TRIZ TF allowed for sharing of the patent dataset, the tech mining software was useful for tracking level of invention and type of invention classifications and the TRIZ TF step of analysis of technological system provides additional insight into terminology and technologies that are useful to the tech mining portion.
- The amount of time required for tech mining depends on the scope of the forecast and level of analysis required. Tech mining can be a relatively quick process or require a significant amount of time.
- Most of the time required to conduct the TRIZ TF is during the level of invention (LOI) evaluation. If it took a forecaster an average of 20 minutes per patent it would take approximately 121 hours to review 364 patents.
- Combing tech mining and TRIZ TF would increase the overall time required to conduct the technology forecast.
- Tech mining and TRIZ TF provide significantly different types of information to the forecaster.
- Tech mining is good at providing information on who is working in an area, identifying the leaders in an area, tracking technology and trends over time and identifying which technology development stage is driving the research but is limited at predicting emerging technologies and future pathways.
- TRIZ TF is good at determining the maturity of a technology system, understanding what component technologies contribute to the technology and identifying likely

future developments but is limited in the more specific technology forecasting questions.

- The hybrid tech mining, TRIZ TF forecast gives the forecaster the ability to address specific forecasting questions using tech mining and look forward at new potential developments using TRIZ TF.
- Both tech mining and TRIZ TF provided accurate forecasts but they differed significantly in the type of forecasting statements that were made.
- Tech mining was able to associate a time period with the predictions because of the use of trend extrapolation while TRIZ TF didn't provide information about when predictions might occur.
- The hybrid tech mining, TRIZ TF forecast offered improvements over either single method.

Additional Findings

- Tech mining is a useful technique for intelligence research.
- The use of 10% patent selection made the descriptive s-curves more challenging to interpret then the data illustrated in the literature that cover all patents.
- The LOI results of the 10% stratified random selection gave similar results to Altshuller's expected percentages for each level of invention.

CHAPTER 7: Recommendations for Future Research

1. The dataset from the study showed that early air filtration media development wasn't being published in WOS and EVillage but from 1985 forward publications began to increase and as of 2000 showed signs of continuing to increase. These publication trends also indicate that patent data may be a better source for forecasting for air filtration media as of 2000. Additional research should be conducted to determine if there has been a shift from industry centric development to basic and applied research or if patent data is still the better source for forecasting for air filtration media.
2. Conduct a second TRIZ TF utilizing additional patterns and lines of evolution to determine if the forecast would change.
3. Investigate which TRIZ patterns and lines of evolution that are most relevant to nonwovens or fiber technologies. Possibly identify patterns and lines used for each invention during LOI evaluation.
4. Further research should be conducted to further develop the evaluation approach used in this study.
5. Conduct a technology forecast for a specific air filtration product type to determine if more detailed information can be extracted from the forecast.
6. Conduct a study to further investigate the use of the maturity mapping for subsystem elements.
7. Conduct a forecast for air filtration media using 2000-2012 data.

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APPENDICES

APPENDIX A

Tech Mining	TRIZ TF
1. Identify MOT questions and decide how to answer them	1. Analysis of the technological system
2. Selection of information sources	2. Technology maturity mapping
3. Search, refine, and data retrieval (iterate)	3. Application of patterns of evolution
4. Clean data	
5. Perform basic and advanced analyses and interpret	
6. Represent the information	
7. Interpretation	

Hybrid Tech Mining and TRIZ TF: Methodology

1. Identify MOT questions and decide how to answer them (TM)
2. Analysis of the technological system (TRIZ TF)
3. Selection of information sources (TM)
4. Search, refine, and data retrieval – iterate (TM)
5. Import into text mining software (TM)
6. Clean data (TM)
7. Basic and advanced analyses and interpret (TM)
8. Technology maturity mapping (TRIZ TF)
9. Application of patterns of evolution (TRIZ TF)
10. Present Information (TM & TRIZ TF)
11. Interpretation (TM & TRIZ TF)

APPENDIX B

Table 35. WOS Vantage Point summary statistics

Number of Records:3110		
Source Database: WOS		
Field	Number of Items	% Coverage
Abstract	2101	67%
Abstract (NLP) (Phrases)	55189	67%
Abstract (NLP) (Words)	25433	67%
Author Affiliations (1st)	1067	60%
Author Affiliations (City and Country)	935	60%
Author Affiliations (Full)	2687	60%
Author Affiliations (Organization and City and Country)	1716	60%
Author Affiliations (Organization Only)	1528	60%
Authors (1st)	2461	100%
Authors (Full Name)	7255	100%
Authors (Initials)	7251	100%
Cited Authors	23652	78%
Cited Journal	11914	78%
Cited Patent	3	0%
Cited Reference Count	98	100%
Cited References	37411	78%
Cited References (DOI)	13929	66%
Cited Year	134	78%
Combined Keywords + Phrases	63502	100%
Conference Date	419	21%
Conference Location	285	21%
Conference Title	438	21%
Database	1	100%
Document Type	12	100%
DOI	1643	52%
Email	56	1%
Genuine Article Number	2697	100%
ISI Doc Delivery Num	2697	100%
ISI Unique Article Identifier	3110	100%
ISSN	860	88%
Issue	126	84%

Table 35 continued

Journal	741	78%
Keywords (author's)	3574	31%
Keywords Plus	3064	41%
Language	13	100%
Number of Author Affiliations (Full)	13	100%
Number of Author Affiliations (Name Only)	11	100%
Number of Authors	19	100%
Pages	40	100%
Publication Date	152	56%
Publication Type	3	100%
Publication Year	76	100%
Publisher	477	99%
Publisher (Short)	477	99%
Publisher Address	600	99%
Publisher City	259	99%
Reprint Address	1992	66%
Reprint Address (City and Country)	759	66%
Reprint Address (no name)	404	18%
Reprint Address (organization)	364	18%
Reprint Author	1973	66%
Source	1102	100%
Source (Start Page)	1240	100%
Source (Volume)	318	89%
Source Title (Abbrev)	922	91%
Subject Category	106	100%
Times Cited	129	100%
Title	3077	100%
Title (NLP) (Phrases)	8147	100%
Title (NLP) (Words)	6484	100%
Web of Science Category	169	100%
~Raw Record	3110	100%

Table 36. EVillage Vantage Point summary statistics

Number of Records:3110		
Source Database: WOS		
Field	Number of Items	% Coverage
Abstract	2101	67%
Abstract (NLP) (Phrases)	55189	67%
Abstract (NLP) (Words)	25433	67%
Author Affiliations (1st)	1067	60%
Author Affiliations (City and Country)	935	60%
Author Affiliations (Full)	2687	60%
Author Affiliations (Organization and City and Country)	1716	60%
Author Affiliations (Organization Only)	1528	60%
Authors (1st)	2461	100%
Authors (Full Name)	7255	100%
Authors (Initials)	7251	100%
Cited Authors	23652	78%
Cited Journal	11914	78%
Cited Patent	3	0%
Cited Reference Count	98	100%
Cited References	37411	78%
Cited References (DOI)	13929	66%
Cited Year	134	78%
Combined Keywords + Phrases	63502	100%
Conference Date	419	21%
Conference Location	285	21%
Conference Title	438	21%
Database	1	100%
Document Type	12	100%
DOI	1643	52%
Email	56	1%
Genuine Article Number	2697	100%
ISI Doc Delivery Num	2697	100%
ISI Unique Article Identifier	3110	100%
ISSN	860	88%
Issue	126	84%
Journal	741	78%

Table 36 continued

Keywords (author's)	3574	31%
Keywords Plus	3064	41%
Language	13	100%
Number of Author Affiliations (Full)	13	100%
Number of Author Affiliations (Name Only)	11	100%
Number of Authors	19	100%
Pages	40	100%
Publication Date	152	56%
Publication Type	3	100%
Publication Year	76	100%
Publisher	477	99%
Publisher (Short)	477	99%
Publisher Address	600	99%
Publisher City	259	99%
Reprint Address	1992	66%
Reprint Address (City and Country)	759	66%
Reprint Address (no name)	404	18%
Reprint Address (organization)	364	18%
Reprint Author	1973	66%
Source	1102	100%
Source (Start Page)	1240	100%
Source (Volume)	318	89%
Source Title (Abbrev)	922	91%
Subject Category	106	100%
Times Cited	129	100%
Title	3077	100%
Title (NLP) (Phrases)	8147	100%
Title (NLP) (Words)	6484	100%
Web of Science Category	169	100%
~Raw Record	3110	100%

Table 37. DII Vantage Point summary statistics

Number of Records:3612		
Source Database: DII		
Field	Number of Items	% Coverage
::Level of Inventiveness	364	10%
::Performance Improvements	364	10%
::Type of Invention	364	10%
Abstract	3578	99%
Abstract (NLP) (Phrases)	53390	99%
Abstract (NLP) (Words)	18343	99%
Abstract ADVANTAGE	1850	51%
Abstract ADVANTAGE (NLP) (Phrases)	8277	51%
Abstract ADVANTAGE (NLP) (Words)	5416	51%
Abstract DESCRIPTION OF DRAWINGS	4	0%
Abstract DESCRIPTION OF DRAWINGS (NLP) (Phrases)	17	0%
Abstract DESCRIPTION OF DRAWINGS (NLP) (Words)	59	0%
Abstract DETAILED DESCRIPTION	4	0%
Abstract DETAILED DESCRIPTION (NLP) (Phrases)	99	0%
Abstract DETAILED DESCRIPTION (NLP) (Words)	225	0%
Abstract EQUIVALENT	2845	31%
Abstract EQUIVALENT (NLP) (Phrases)	28680	31%
Abstract EQUIVALENT (NLP) (Words)	12166	31%
Abstract NOVELTY	535	14%
Abstract NOVELTY (NLP) (Phrases)	4461	14%
Abstract NOVELTY (NLP) (Words)	3346	14%
Abstract USE	1192	33%
Abstract USE (NLP) (Phrases)	3320	33%
Abstract USE (NLP) (Words)	2831	33%
Abstract USE/ADVANTAGE	854	23%
Abstract USE/ADVANTAGE (NLP) (Phrases)	6076	23%
Abstract USE/ADVANTAGE (NLP) (Words)	4844	23%
Application Dates	3442	89%
Application Numbers (long)	9452	89%
Application Years	43	89%
Basic Patent Country	32	98%
Basic Patent Date	2148	97%
Basic Patent Number	3561	98%

Table 37 continued

Basic Patent Number (long)	3561	98%
Basic Patent Year	31	98%
Cited (Other)	2918	16%
Cited Patent Assignee Codes	3992	44%
Cited Patent Assignees	5340	44%
Cited Patent Inventors	9698	34%
Cited Patent Numbers	16863	47%
Derwent Accession Number	3612	100%
Derwent Classifications	271	100%
Derwent Classifications (full)	271	100%
Designated States	95	20%
Designated States National	86	9%
Designated States Regional	43	20%
Family Member Countries	43	98%
Family Member Dates	4872	98%
Family Member Numbers	9934	98%
Family Member Numbers (long)	12269	98%
Family Member Years	42	98%
Field of Search	3727	36%
File Segment	5	100%
International Classifications 8	3189	99%
International Classifications 8 (4-digit)	366	99%
Inventors	3529	49%
Key	3613	100%
Manual Codes	1832	96%
Patent Assignee Codes	1896	100%
Patent Assignees	2492	100%
Patent Assignees (long)	2500	100%
Priority Countries	54	99%
Priority Dates	3143	99%
Priority Numbers	3549	99%
Priority Numbers (long)	4704	99%
Priority Years	49	99%
Publication Type	1	1%
Temp Year Field	53	99%
Title	3612	100%
Title (NLP) (Phrases)	13637	100%

Table 37 continued

Title (NLP) (Words)	6556	100%
US Patent Dates	883	30%
US Patent Numbers	1378	30%
US Patent Numbers (long)	1405	30%
US Patent Years	39	30%
~Raw Record	3660	100%

Table 38. Business Source Complete Vantage Point summary statistics

Number of Records:479		
Source Database: Business Source Complete		
Field	Number of Items	% Coverage
Abstract	476	100%
Abstract (NLP) (Phrases)	4633	100%
Abstract (NLP) (Words)	5223	100%
Author	206	43%
Document type	4	100%
Keywords	564	90%
Keywords (Cleaned)	562	90%
Notes	479	100%
Publication Date	297	100%
Publication Year	18	100%
Publisher	47	57%
Source (End Page)	29	6%
Source (ISSN/ISBN)	136	99%
Source (Issue)	51	89%
Source (Start Page)	140	100%
Source (Std Abbrev)	137	100%
Source (Volume)	137	88%
Title	411	99%
Title (NLP) (Phrases)	723	98%
Title (NLP) (Words)	1214	99%
Type of Reference	3	100%
URL	479	100%
~Raw Record	479	100%

Table 39. Annual and cumulative data for all databases

Publication Year	EIVillage annual	EIVillage cumulative	DII annual	DII cumulative	WOS annual	WOS cumulative	BS annual	BS cumulative
1907					1	1		
1909					1	2		
1913					1	3		
1919	1	1			2	5		
1920	4	5						
1921	3	8			1	6		
1922	1	9						
1923	6	15			1	7		
1924	2	17						
1925	3	20			1	8		
1926	4	24			1	9		
1927	2	26						
1928	7	33			1	10		
1929	11	44			2	12		
1930	7	51			2	14		
1931	9	60			2	16		
1932	5	65			2	18		
1933	8	73			2	20		
1934	1	74						
1935	3	77						
1936	9	86						
1937	6	92			2	22		
1938	7	99			2	24		
1939	7	106			2	26		
1940	5	111			1	27		
1941	11	122			4	31		
1942	7	129						
1943	12	141			1	32		
1944	6	147						
1945	11	158			1	33		
1946	10	168			1	34		
1947	8	176			1	35		
1948	6	182			2	37		
1949	5	187			1	38		
1950	8	195			2	40		

Table 39 continued

1951	5	200			5	45		
1952	11	211			3	48		
1953	16	227			9	57		
1954	11	238			6	63		
1955	10	248			3	66		
1956	17	265			7	73		
1957	10	275			4	77		
1958	15	290			6	83		
1959	7	297			4	87		
1960	10	307			3	90		
1961	6	313			8	98		
1962	19	332			5	103		
1963	7	339			9	112		
1964	12	351			8	120		
1965	26	377			16	136		
1966	23	400			13	149		
1967	11	411	1	1	20	169		
1968	18	429			22	191		
1969	16	445			25	216		
1970	20	465			20	236		
1971	33	498			33	269		
1972	28	526	2	3	19	288		
1973	61	587	2	5	27	315		
1974	51	638	28	33	31	346		
1975	42	680	39	72	26	372		
1976	38	718	53	125	15	387		
1977	47	765	36	161	29	416		
1978	53	818	42	203	22	438		
1979	46	864	46	249	28	466		
1980	40	904	73	322	32	498		
1981	55	959	72	394	34	532		
1982	36	995	67	461	32	564		
1983	57	1052	82	543	36	600	1	1
1984	75	1127	73	616	35	635		1
1985	60	1187	119	735	31	666	1	2
1986	95	1282	118	853	31	697	3	5
1987	43	1325	126	979	19	716	3	8

Table 39 continued

1988	49	1374	109	1088	34	750	5	13
1989	49	1423	163	1251	24	774	2	15
1990	51	1474	137	1388	43	817	9	24
1991	54	1528	135	1523	148	965	6	30
1992	55	1583	168	1691	130	1095	5	35
1993	94	1677	185	1876	153	1248	33	68
1994	103	1780	181	2057	200	1448	37	105
1995	66	1846	210	2267	206	1654	53	158
1996	170	2016	196	2463	255	1909	52	210
1997	187	2203	222	2685	298	2207	83	293
1998	162	2365	277	2962	307	2514	71	364
1999	130	2495	354	3316	325	2839	53	417
2000	154	2649	224	3540	271	3110	61	478

Table 40. WOS and EVillage cumulative data covering media and nonwoven

Publication Year	WOS media or nonwoven publications cumulative	Evillage media or nonwovens publications cumulative
1951	1	0
1952		1
1954		2
1955	2	3
1956		4
1958		6
1959		7
1960		8
1962		10
1963		11
1964		13
1965		16
1966		17
1967	3	18
1968	4	19
1969	5	22
1970	6	25
1971	8	29

Table 40 continued

1972		33
1973		36
1974	12	40
1975	15	45
1976		52
1977	16	58
1978		66
1979	17	71
1980	19	76
1981		80
1982	20	81
1983	21	83
1984	23	90
1985	26	97
1986	27	116
1987	28	120
1988	30	129
1989	31	133
1990	37	139
1991	61	146
1992	80	152
1993	114	167
1994	156	178
1995	196	189
1996	242	218
1997	320	258
1998	391	288
1999	456	300
2000	503	315

Table 41. JMP Gompertz fit report glass fiber

JMP results: Glass fiber

Model Comparison

Model		AICc	BIC	SSE	MSE	RMSE	R-Square
Gompertz 3P	—	161.99356	165.35873	443.22833	18.467847	4.2974233	0.9984278

Gompertz 3P: Summary of Fit

AICc	161.99356
BIC	165.35873
SSE	443.22833
MSE	18.467847
RMSE	4.2974233
R-Square	0.9984278

Parameter Estimates

Parameter	Estimate	Std Error	Lower 95%	Upper 95%
Asymptote	643.57493	42.584296	560.11124	727.03862
Growth Rate	0.0746003	0.0038746	0.0670063	0.0821943
Inflection Point	1994.8902	0.9217967	1993.0835	1996.6969

Correlation of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.0000	-0.9763	0.9971
Growth Rate	-0.9763	1.0000	-0.9814
Inflection Point	0.9971	-0.9814	1.0000

Covariance of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1813.42	-0.1611	39.1384
Growth Rate	-0.1611	0.0000	-0.0035
Inflection Point	39.1384	-0.0035	0.8497

Table 42. JMP Gompertz report wetlaid

JMP results: Wetlaid

Model Comparison

Model		AICc	BIC	SSE	MSE	RMSE	R-Square
Gompertz 3P	——	42.113612	44.720565	5.3327016	0.2539382	0.5039228	0.9574518

Gompertz 3P: Summary of Fit

AICc	42.113612
BIC	44.720565
SSE	5.3327016
MSE	0.2539382
RMSE	0.5039228
R-Square	0.9574518

Parameter Estimates

Parameter	Estimate	Std Error	Lower 95%	Upper 95%
Asymptote	9.7183875	1.5160076	6.7470672	12.689708
Growth Rate	0.1076164	0.0219379	0.0646188	0.150614
Inflection Point	1988.4835	1.7465218	1985.0604	1991.9066

Correlation of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.0000	-0.9531	0.9809
Growth Rate	-0.9531	1.0000	-0.9257
Inflection Point	0.9809	-0.9257	1.0000

Covariance of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	2.2983	-0.0317	2.5972
Growth Rate	-0.0317	0.0005	-0.0355
Inflection Point	2.5972	-0.0355	3.0503

Table 43. JMP Gompertz report spunbond

JMP results: Spunbond

Model Comparison

Model		AICc	BIC	SSE	MSE	RMSE	R-Square
Gompertz 3P	—	77.688018	79.366107	30.146679	1.6748155	1.2941466	0.9816381

Gompertz 3P: Summary of Fit

AICc	77.688018
BIC	79.366107
SSE	30.146679
MSE	1.6748155
RMSE	1.2941466
R-Square	0.9816381

Parameter Estimates

Parameter	Estimate	Std Error	Lower 95%	Upper 95%
Asymptote	18310.944	115896.25	-208841.5	245463.42
Growth Rate	0.017359	0.015462	-0.012946	0.0476641
Inflection Point	2106.5566	152.06432	1808.516	2404.5972

Correlation of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.0000	-0.9990	0.9996
Growth Rate	-0.9990	1.0000	-0.9999
Inflection Point	0.9996	-0.9999	1.0000

Covariance of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.3e+10	-1790.2	1.76e+7
Growth Rate	-1790.2	0.0002	-2.3509
Inflection Point	1.76e+7	-2.3509	23123.6

Solution: Gompertz limit 400

SSE	DFE	MSE	RMSE
42.252216719	19	2.2238009	1.4912414

Parameter	Estimate	ApproxStdErr
a	400	0
b	0.0376113346	0.00173863
c	2024.9885828	1.38079407

Solved By:

Analytic Gauss-Newton

Table 44. JMP Gompertz report meltblow

JMP results: Meltlblow

Model Comparison

Model		AICc	BIC	SSE	MSE	RMSE	R-Square
Gompertz 3P	——	140.29698	143.17248	268.50724	12.204875	3.4935476	0.9886525

Gompertz 3P: Summary of Fit

AICc	140.29698
BIC	143.17248
SSE	268.50724
MSE	12.204875
RMSE	3.4935476
R-Square	0.9886525

Parameter Estimates

Parameter	Estimate	Std Error	Lower 95%	Upper 95%
Asymptote	259.5834	78.382398	105.95672	413.21008
Growth Rate	0.0892299	0.0168548	0.0561951	0.1222647
Inflection Point	1999.6528	3.2275293	1993.327	2005.9787

Correlation of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.0000	-0.9823	0.9979
Growth Rate	-0.9823	1.0000	-0.9896
Inflection Point	0.9979	-0.9896	1.0000

Covariance of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	6143.80	-1.2977	252.440
Growth Rate	-1.2977	0.0003	-0.0538
Inflection Point	252.440	-0.0538	10.4169

Table 45. JMP Gompertz report needle-punch

JMP results: Needle-punch

Model Comparison

Model		AICc	BIC	SSE	MSE	RMSE	R-Square
Gompertz 3P	—	123.78582	126.91344	121.54202	5.2844357	2.29879	0.9945445

Gompertz 3P: Summary of Fit

AICc	123.78582
BIC	126.91344
SSE	121.54202
MSE	5.2844357
RMSE	2.29879
R-Square	0.9945445

Parameter Estimates

Parameter	Estimate	Std Error	Lower 95%	Upper 95%
Asymptote	172.80411	18.239501	137.05535	208.55288
Growth Rate	0.0727538	0.0066438	0.0597321	0.0857754
Inflection Point	1992.8798	1.5516732	1989.8385	1995.921

Correlation of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.0000	-0.9754	0.9966
Growth Rate	-0.9754	1.0000	-0.9782
Inflection Point	0.9966	-0.9782	1.0000

Covariance of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	332.679	-0.1182	28.2063
Growth Rate	-0.1182	0.0000	-0.0101
Inflection Point	28.2063	-0.0101	2.4077

Table 46. JMP Gompertz report split fiber or film

JMP results: Split fiber or film

Model Comparison

Model		AICc	BIC	SSE	MSE	RMSE	R-Square
Gompertz 3P	—	58.874205	58.328196	17.940787	1.3800605	1.1747598	0.9721848

Gompertz 3P: Summary of Fit

AICc	58.874205
BIC	58.328196
SSE	17.940787
MSE	1.3800605
RMSE	1.1747598
R-Square	0.9721848

Parameter Estimates

Parameter	Estimate	Std Error	Lower 95%	Upper 95%
Asymptote	49.216694	25.184751	-0.144511	98.577899
Growth Rate	0.127097	0.0434559	0.041925	0.2122689
Inflection Point	1999.1113	3.9431654	1991.3828	2006.8397

Correlation of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.0000	-0.9808	0.9977
Growth Rate	-0.9808	1.0000	-0.9877
Inflection Point	0.9977	-0.9877	1.0000

Covariance of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	634.272	-1.0734	99.0840
Growth Rate	-1.0734	0.0019	-0.1692
Inflection Point	99.0840	-0.1692	15.5486

Table 47. JMP Gompertz report membrane

JMP results: Membrane

Model Comparison

Model		AICc	BIC	SSE	MSE	RMSE	R-Square
Gompertz 3P	——	121.39385	124.75902	98.53306	4.1055441	2.0262142	0.9978582

Gompertz 3P: Summary of Fit

AICc	121.39385
BIC	124.75902
SSE	98.53306
MSE	4.1055441
RMSE	2.0262142
R-Square	0.9978582

Parameter Estimates

Parameter	Estimate	Std Error	Lower 95%	Upper 95%
Asymptote	888.92565	239.00854	420.47751	1357.3738
Growth Rate	0.0461428	0.0047914	0.0367518	0.0555338
Inflection Point	2013.5974	4.4417468	2004.8917	2022.303

Correlation of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.0000	-0.9916	0.9983
Growth Rate	-0.9916	1.0000	-0.9972
Inflection Point	0.9983	-0.9972	1.0000

Covariance of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	57125.1	-1.1356	1059.80
Growth Rate	-1.1356	0.0000	-0.0212
Inflection Point	1059.80	-0.0212	19.7291

Solution: Limited 400

SSE	DFE	MSE	RMSE
169.39655559	25	6.7758622	2.6030486

Parameter	Estimate	ApproxStdErr
a	400	0
b	0.0663552204	0.00117945
c	2001.5021715	0.15641224

Solved By:

Analytic Gauss-Newton

Table 48. JMP Gompertz report electrostatics

JMP results: Electret or electrostatic

Model Comparison

Model		AICc	BIC	SSE	MSE	RMSE	R-Square
Gompertz 3P	—	174.56516	178.36768	500.48307	19.249349	4.387408	0.9994773

Gompertz 3P: Summary of Fit

AICc	174.56516
BIC	178.36768
SSE	500.48307
MSE	19.249349
RMSE	4.387408
R-Square	0.9994773

Parameter Estimates

Parameter	Estimate	Std Error	Lower 95%	Upper 95%
Asymptote	1804.8898	122.74272	1564.3185	2045.4611
Growth Rate	0.0602487	0.0022913	0.0557579	0.0647396
Inflection Point	2002.0187	1.0265124	2000.0068	2004.0306

Correlation of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.0000	-0.9850	0.9980
Growth Rate	-0.9850	1.0000	-0.9924
Inflection Point	0.9980	-0.9924	1.0000

Covariance of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	15065.8	-0.2770	125.747
Growth Rate	-0.2770	0.0000	-0.0023
Inflection Point	125.747	-0.0023	1.0537

Solution: Limit 1000

SSE	DFE	MSE	RMSE
3451.5996278	27	127.83702	11.306504

Parameter	Estimate	ApproxStdErr
a	1000	0
b	0.0892711315	0.00161324
c	1994.0071474	0.09607942

Solved By:

Analytic Gauss-Newton

Table 49. JMP Gompertz report composite

JMP results: Composite

Model Comparison

Model		AICc	BIC	SSE	MSE	RMSE	R-Square
Gompertz 3P	—	120.61336	123.74099	107.58084	4.6774278	2.1627362	0.9978577

Gompertz 3P: Summary of Fit

AICc	120.61336
BIC	123.74099
SSE	107.58084
MSE	4.6774278
RMSE	2.1627362
R-Square	0.9978577

Parameter Estimates

Parameter	Estimate	Std Error	Lower 95%	Upper 95%
Asymptote	8632.9128	7296.7823	-5668.518	22934.343
Growth Rate	0.026574	0.004658	0.0174445	0.0357034
Inflection Point	2052.5117	17.016545	2019.1599	2085.8635

Correlation of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.0000	-0.9971	0.9990
Growth Rate	-0.9971	1.0000	-0.9995
Inflection Point	0.9990	-0.9995	1.0000

Covariance of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	5.32e+7	-33.889	124042
Growth Rate	-33.889	0.0000	-0.0792
Inflection Point	124042	-0.0792	289.563

Solution: Limit 400

SSE	DFE	MSE	RMSE
515.43552992	24	21.47648	4.6342724

Parameter	Estimate	ApproxStdErr
a	400	0
b	0.0736638586	0.0022238
c	2000.3998475	0.22741693

Solved By:

Analytic Gauss-Newton

Table 50. JMP Gompertz report HEPA filtration

JMP results: HEPA filtration

Model Comparison

Model		AICc	BIC	SSE	MSE	RMSE	R-Square
Gompertz 3P	—	179.02787	182.39303	832.95967	34.706653	5.8912353	0.9983434

Gompertz 3P: Summary of Fit

AICc	179.02787
BIC	182.39303
SSE	832.95967
MSE	34.706653
RMSE	5.8912353
R-Square	0.9983434

Parameter Estimates

Parameter	Estimate	Std Error	Lower 95%	Upper 95%
Asymptote	2017.4325	350.0126	1331.4204	2703.4446
Growth Rate	0.0507598	0.0040209	0.042879	0.0586406
Inflection Point	2007.9953	2.8316062	2002.4454	2013.5451

Correlation of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	1.0000	-0.9893	0.9982
Growth Rate	-0.9893	1.0000	-0.9958
Inflection Point	0.9982	-0.9958	1.0000

Covariance of Estimates

	Asymptote	Growth Rate	Inflection Point
Asymptote	122509	-1.3923	989.319
Growth Rate	-1.3923	0.0000	-0.0113
Inflection Point	989.319	-0.0113	8.0180

Solution: Limit 1000

SSE	DFE	MSE	RMSE
1921.0008325	25	76.840033	8.7658447

Parameter	Estimate	ApproxStdErr
a	1000	0
b	0.0744136451	0.00133262
c	1997.5799775	0.11909619

Solved By:

Analytic Gauss-Newton

Table 51. TRIZ patent results

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
US 3297460 A 19670110	1967	USA	FMC CORP (FMCC)	2	dust holding capacity; filter life	finishing
DE2048006-A 197115	1971	Germany	ASAHI CHEM IND CO LTD (ASAH)	4	improved manufacturing	web formation and bonding
DE 2164262 A 19720810	1972	Germany	TEIJIN LTD (TEIJ)	3	filtration efficiency	raw material
DE2308242-A 197338	1973	Germany	ESSO RES & ENG CO (ESSO)	4	improved manufacturing	web formation and bonding
DE2137309-A 197308	1973	Germany	PUROLATOR FILTER GMBH (PURO)	2	improved manufacturing	web formation and bonding
US 3853510 A 19741210	1974	USA	SYSTEMS DISCIPLINE INC (SYST-N)	2	filter life	filtration device
US 3807150 A 19740430	1974	USA	HEPA CORP (HEPA-N)	3	filtration efficiency	filtration device
US 3807147 A 19740430	1974	USA	JOHNSON & JOHNSON (JOHJ)	2	filtration efficiency; filter life	filtration device
DE 2407329 A 19740905	1974	Germany	CARELLO & C SPA FAUSTO (CARE-N)	1	improved manufacturing	filtration device; composite of fibers or structure
US 3880625 A 19750429	1975	USA	MOORE & HANKS CO (MOOR-N)	1	filtration efficiency	filtration device
BE 824562 A 19750722	1975	Belgium	MINNESOTA MINING CO (MINN)	4	filter resistance to air flow (initial pressure drop); filter life	web formation and bonding
BE 827077 A 19750716	1975	Belgium	MINNESOTA MINING CO (MINN); VERTO NV (VERT-N)	5	filtration efficiency	web formation and bonding; composite of fibers or structure; finishing
GB 1405138 A 19750903	1975	UK	UK ATOMIC ENERGY AUTHORITY (UKAT)	2	filtration efficiency	testing

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
US 3937860 A 19760210	1976	USA	STEVENS & CO INC J P (STEV)	1	filter life	composite of fibers or structure
DD 118233 A 19760220	1976	Germany	MITOP VYROBA PLSTI (MITO-N)	2	energy costs/usage	composite of fibers or structure
US 3953566 A 19760427	1976	USA	GORE & ASSOC INC W L (GORE)	3	filtration efficiency; filter resistance to air flow (initial pressure drop)	raw material
DE 2460764 A 19760701	1976	Germany	CHEM-ANLAG BISCHOFS (BISC-N); REUTER TECHNOLOGIE GMBH (REUT-N)	2	filtration efficiency	raw material
US 3959421 A 19760525	1976	USA	KIMBERLY CLARK CORP (KIMB)	3	improved manufacturing	web formation and bonding
BE 849766 A 19770622	1977	Belgium	MONSANTO CO (MONS)	3	filtration efficiency	filtration device
US 4007114 A 19770208	1977	USA	AMF INC (AMMA)	2	filtration efficiency	finishing
US 4041203 A 19770809	1977	USA	KIMBERLY CLARK CORP (KIMB)	4	improved manufacturing	web formation and bonding
US 4011067 A 19770308	1977	USA	MINNESOTA MINING CO (MINN)	3	filtration efficiency; filter resistance to air flow (initial pressure drop); filter life; energy costs/usage	web formation and bonding; composite of fibers or structure
US 4102785 A 19780725	1978	USA	WHATMAN REEVE ANGEL LTD (WHAT-N)	2	improved manufacturing	filtration device; web formation and bonding
US 4118531 A 19781003	1978	USA	MINNESOTA MINING CO (MINN)	4		web formation and bonding
US 4100324 A 19780711	1978	USA	KIMBERLY CLARK CORP (KIMB)	4	improved manufacturing	web formation and bonding

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
BE 862156 A 19780622	1978	Belgium	MINNESOTA MINING CO (MINN); VERTO NV (VERT-N)	3	filtration efficiency	web formation and bonding
US 4093437 A 19780606	1978	USA	NIPPONDENSO CO LTD (NPDE)	2		
US 4160059 A 19790703	1979	USA	HONSHU SEISHI KK (HONP)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
US 4141703 A 19790227	1979	USA	MULCHI C L (MULC-I)	3	filter life	filtration device
JP 54147168 A 19791117	1979	Japan	TOYOTA JIDOSHA KK (TOYT)	2	filtration efficiency	filtration device
US 4164400 A 19790814	1979	USA	SCOTT/CHATHAM CO (SCOT-N)	2	filter life	web formation and bonding; composite of fibers or structure
DE 2904170 A 19790809	1979	Germany	MINNESOTA MINING CO (MINN)	4	filtration efficiency	web formation and bonding; raw material; composite of fibers or structure
JP 55111816 A 19800828	1980	Japan	KANAI H (KANA-I)	1		composite of fibers or structure
US 4187390 A 19800205	1980	USA	GORE & ASSOC INC W L (GORE)	3	filter life	raw material; composite of fibers or structure
US 4233042 A 19801111	1980	USA	INCOM INT INC (INCO-N)	2	filter resistance to air flow (initial pressure drop); energy costs/usage	filtration device

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
CA 1074712 A 19800401	1980	Canada	FLANDERS FILTERS (FLAN-N)	1		filtration device
US 4211661 A 19800708	1980	USA	CHAVE & EARLEY (CHAV-N)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	web formation and bonding; composite of fibers or structure
JP 80001803 B 19800117	1980	Japan	SAKAI G (SAKA-I)	2	filtration efficiency	web formation and bonding; composite of fibers or structure
DE 2847941 A 19800514	1980	Germany	FRAUNHOFER-GES FORD ANGE (FRAU)	1	filtration efficiency	testing
US 4286977 A 19810901	1981	USA	KLEIN M (KLEI-I)	2	filter life	composite of fibers or structure
FR 2483806 A 19811211	1981	France	MASUDA S (MASU-I); MIDORI ANZEN CO LTD (MIDO-N)	2	filtration efficiency; filter life	filtration device
JP 56166912 A 19811222	1981	Japan	HITACHI LTD (HITA)	1	improved manufacturing	filtration device
FR 2477031 A 19810904	1981	France	DRAEGERWERK AG (DRAG)	1	filter life	filtration device
JP 56010312 A 19810202	1981	Japan	MITSUI PETROCHEM IND CO LTD (MITC); NITTA BELT KK (NIBD)	2	filtration efficiency	filtration device; composite of fibers or structure
FR 2481719 A 19811106	1981	France	KIMBERLY CLARK CORP (KIMB)	4	improved manufacturing	web formation and bonding
US 4257791 A 19810324	1981	USA	LYDALL INC (LYDA-N)	1	filter life	web formation and bonding; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
US 4324574 A 19820413	1982	USA	DU PONT DE NEMOURS & CO E I (DUPO)	3	filtration efficiency	composite of fibers or structure
GB 2082642 A 19820310	1982	UK	NINSOKU Y (NINS-I); OSHITARI Y (OSHI-I)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
JP 57105217 A 19820630	1982	Japan	NITTA BELT KK (NIBD)	2	filter resistance to air flow (initial pressure drop)	composite of fibers or structure
JP 82032610 B 19820712	1982	Japan	KANAI H (KANA-I)	1	filtration efficiency	composite of fibers or structure
US 4322230 A 19820330	1982	USA	DONALDSON CO INC (DOND)	2		filtration device
EP 60687 A 19820922	1982	EPO	JOHNSON & JOHNSON (JOHJ); SURGIKOS INC (SURG-N)	4	filtration efficiency	finishing
US 4358504 A 19821109	1982	USA	DEXTER CORP (DEXC)	1	filtration efficiency	finishing
EP 53879 A 19820616	1982	EPO	NIPPONDENSO CO LTD (NPDE); TOYO BOSEKI KK (TOYM)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	web formation and bonding; composite of fibers or structure
JP 58030318 A 19830222	1983	Japan	KOKEN KK (KOKE)	1	dust holding capacity	composite of fibers or structure
JP 58006221 A 19830113	1983	Japan	ZEN T (ZENT-I)	1	filtration efficiency	composite of fibers or structure
JP 58101721 A 19830617	1983	Japan	TOA NENRYO KOGYO KK (TOFU)	2	filtration efficiency	composite of fibers or structure; finishing

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
JP 58128120 A 19830730	1983	Japan	SHINOTARI Y (SHIN-I)	1		raw material; composite of fibers or structure
EP 96597 A 19831221	1983	EPO	FLANDERS FILTERS (FLAN-N)	1	improved manufacturing	filtration device
US 4416675 A 19831122	1983	USA	CORNING GLASS WORKS (CORG)	1	filtration efficiency	filtration device; composite of fibers or structure
JP 58132197 A 19830806	1983	Japan	AWA SEISHI KK (AWAS-N)	1	filter life	finishing
EP 88533 A 19830914	1983	EPO	3M CO (MINN); KIMBERLY-CLARK CORP (KIMB)	3	filtration efficiency	web formation and bonding; composite of fibers or structure
DE 3304349 A 19840809	1984	Germany	BLUCHER H (BLUC-I); BLUCHER H VON (VBLU-I)	2	filtration efficiency; filter resistance to air flow (initial pressure drop); filter life	composite of fibers or structure
US 4459332 A 19840710	1984	USA	AMERICAN CYANAMID CO (AMCY)	2	filtration efficiency	composite of fibers or structure
US 4427422 A 19840124	1984	USA	TERRELL MACH CO (TERR-N)	1	filtration efficiency	filtration device
EP 98007 A 19840111	1984	EPO	ATASI CORP (ATAS-N)	3	filtration efficiency	filtration device; composite of fibers or structure
WO 8404467 A 19841122	1984	WIPO	IND ARBETSHYGIEN SO (INAR-N); KRANTZ A (KRAN-I)	2	filter life	filtration device; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
DE 3332324 A 19840315	1984	Germany	DOMNICK HUNTER FILTERS LTD (DOMN-N)	2	improved manufacturing	filtration device; composite of fibers or structure
WO 8403193 A 19840816	1984	WIPO	3M CO (MINN); KLAASE P T A (KLAA-I); MINNESOTA MINING & MFR CO (MINN); NEDERLAND ORG TNO (NEDE)	2	filtration efficiency	finishing
US 4433024 A 19840221	1984	USA	3M CO (MINN)	2	filtration efficiency	web formation and bonding; composite of fibers or structure
EP 161790 A 19851121	1985	EPO	3M CO (MINN)	3	filtration efficiency	composite of fibers or structure
JP 60161712 A 19850823	1985	Japan	HITACHI LTD (HITA)	1	filtration efficiency	composite of fibers or structure
WO 8503013 A 19850718	1985	WIPO	HUGHES AIRCRAFT CO (HUGA)	3	filtration efficiency; filter resistance to air flow (initial pressure drop); filter life	composite of fibers or structure
DE 3404395 A 19850814	1985	Germany	MIELE & CIE (MIEL)	2	filtration efficiency; filter life	composite of fibers or structure; finishing
EP 160497 A 19851106	1985	EPO	MITSUI PETROCHEM IND CO LTD (MITC)	3	filtration efficiency; filter resistance to air flow (initial pressure drop)	raw material; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
BE 902186 A 19850731	1985	Belgium	ENVIRONMENTAL AIR (ENVI-N); ENVIRONMENTAL AIR CONTROL (ENVI-N)	2	filtration efficiency; energy costs/usage	filtration device
ZA 8409436 A 19850530	1985	South Africa	GORE & ASSOC INC W L (GORE)	2	improved manufacturing	filtration device
US 4536440 A 19850820	1985	USA	3M CO (MINN)	2	filter resistance to air flow (initial pressure drop)	filtration device; web formation and bonding
DE 3509857 A 19850919	1985	Germany	TOYO BOSEKI KK (TOYM)	2	filtration efficiency	finishing
EP 141674 A 19850515	1985	EPO	CELANESE CORP (CELA)	1	improved manufacturing	web formation and bonding
JP 60102913 A 19850607	1985	Japan	KANAI H (KANA-I)	2	filtration efficiency	web formation and bonding
DE 3504187 A 19850912	1985	Germany	FREUDENBERG FA CARL (FREU)	3	filtration efficiency; dust holding capacity	web formation and bonding; finishing
GB 2172814 A 19861001	1986	UK	PIPERCROSS LTD (PIPE-N)	1	filter life	composite of fibers or structure
JP 61103512 A 19860522	1986	Japan	NAKAMURA H (NAKA-I)	1	filter life	composite of fibers or structure
US 4565727 A 19860121	1986	USA	AMERICAN CYANAMID CO (AMCY)	1	filter life	composite of fibers or structure
DE 3433622 A 19860320	1986	Germany	FILTERWERK MANN & HUMMEL GMBH (FILW)	1	filter life	filtration device
US 4581046 A 19860408	1986	USA	US DEPT ENERGY (USAT)	1	filtration efficiency; filter life	filtration device
DE 3444652 A 19860612	1986	Germany	HOLTER H (HOLT-I)	2		filtration device

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
DE 3518665 A 19861204	1986	Germany	HOELTER H (HOEL-I); HOLTER H (HOLT-I)	1		filtration device; raw material
US 4629483 A 19861216	1986	USA	REFRACTRON CORP (REFR-N)	2	filtration efficiency; filter life	filtration device; web formation and bonding
EP 182512 A 19860528	1986	EPO	TORAY IND INC (TORA)	2	filtration efficiency; dust holding capacity	finishing
US 4612237 A 19860916	1986	USA	DU PONT DE NEMOURS & CO E I (DUPO)	1	filter life	web formation and bonding
JP 61268313 A 19861127	1986	Japan	NIPPON MUKI KK (NIMU)	1	filter resistance to air flow (initial pressure drop)	web formation and bonding; composite of fibers or structure
JP 61133110 A 19860620	1986	Japan	KANAI H (KANA-I)	2	improved manufacturing	web formation and bonding; composite of fibers or structure
JP 62110719 A 19870521	1987	Japan	KURARAY CO LTD (KURS)	1	dust holding capacity; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
JP 62083017 A 19870416	1987	Japan	TOYOBO KK (TOYM)	2	filter resistance to air flow (initial pressure drop); filter life	composite of fibers or structure
US 4650506 A 19870317	1987	USA	DONALDSON CO INC (DOND)	3	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
DE 3614949 A 19871105	1987	Germany	HEIMBACH GMBH & CO THOMAS JOSEF (HEIM); HEIMBACH GMBH THOMAS JOSEF (HEIM)	1	filter life	composite of fibers or structure
JP 62140614 A 19870624	1987	Japan	MATSUSHITA DENKI SANGYO KK (MATU)	1	filtration efficiency	composite of fibers or structure
JP 62069974 A 19870331	1987	Japan	DAICEL CHEM IND LTD (DAIL)	2	filtration efficiency	raw material
SU 1351632 A 19871115	1987	Soviet Union	AS BELO METAL POLYM (ABME-R)	1	filter resistance to air flow (initial pressure drop)	raw material; composite of fibers or structure
EP 246917 A 19871125	1987	EPO	GORE & ASSOC INC W L (GORE); JAPAN GORE TEX INC (NIGO); OSHITARI LAB INC (OSHI-N); OSHITARI Y (OSHI-I)	4	filtration efficiency	raw material; composite of fibers or structure
GB 2186211 A 19870812	1987	UK	MARSHALL D A G (MARS-I)	1		filtration device
US 4699681 A 19871013	1987	USA	D-MARK INC (DMAR-N)	2	filter resistance to air flow (initial pressure drop)	web formation and bonding
AU 8772439 A 19871112	1987	Australia	KIMBERLY CLARK CORP (KIMB)	4	filtration efficiency; filter resistance to air flow (initial pressure drop)	web formation and bonding; composite of fibers or structure
EP 246811 A 19871125	1987	EPO	BRITISH TECHNOLOGY GROUP LTD (BTGB); NAT RES DEV CORP (NATR)	2	filtration efficiency	web formation and bonding; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
US 4701197 A 19871020	1987	USA	ALLIED CORP (ALLC); ALLIED-SIGNAL INC (ALLC)	2	improved manufacturing	web formation and bonding; composite of fibers or structure
US 4759782 A 19880726	1988	USA	PALL CORP (PALL)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
US 4765812 A 19880823	1988	USA	ALLIED-SIGNAL INC (ALLC)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
JP 63100911 A 19880506	1988	Japan	MATSUSHITA DENKI SANGYO KK (MATU)	1	filtration efficiency	composite of fibers or structure
JP 63044916 A 19880225	1988	Japan	SANYO KOKUSAKU PULP CO (SAOK)	1	filtration efficiency	composite of fibers or structure
DE 3631804 A 19880324	1988	Germany	ALTENBURGER ELTRN (ALTE-N)	2	improved manufacturing	raw material
WO 8808463 A 19881103	1988	WIPO	ALLIED CORP (ALLC)	3	filtration efficiency	raw material
JP 63185424 A 19880801	1988	Japan	TOSHIBA KK (TOKE)	1		raw material
EP 269462 A 19880601	1988	EPO	UNITIKA LTD (NIRA)	2	filtration efficiency; filter life	raw material; composite of fibers or structure
US 4737173 A 19880412	1988	USA	AMWAY CORP (AMWA-N)	4	filter life	filtration device
US 4732592 A 19880322	1988	USA	SPENGLER C W (SPEN-I)	2		filtration device
US 4717401 A 19880105	1988	USA	CASCO PRODUCTS CORP (CASC-N)	1	filtration efficiency	filtration device
JP 1245820 A 19891002	1989	Japan	SEIBU DENKI KOGYO KK (SEIB-N)	1	filter life	composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
JP 1304022 A 19891207	1989	Japan	IBIDEN CO LTD (IBIG)	2	filtration efficiency	composite of fibers or structure
DE 3813563 A 19891102	1989	Germany	DE RUITER E (DRUI-I); MHB FILTRATION GMBH & CO KG (MHBF-N); VON BLUCHER H (VBLU-I); VON BLUECHER H (VBLU-I)	3	filtration efficiency	composite of fibers or structure
JP 1159013 A 19890622	1989	Japan	SANWAKO KK (SANW-N)	1	filtration efficiency	composite of fibers or structure
JP 1293113 A 19891127	1989	Japan	DAIKIN KOGYO KK (DAIK)	1	filtration efficiency	composite of fibers or structure
EP 338479 A 19891025	1989	EPO	GESSNER & CO GMBH (GESS-N); STEINBEIS GESSNER GMBH (STEI-N)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
US 4878929 A 19891107	1989	USA	NELSON IND INC (NELS-N)	2	filtration efficiency; filter resistance to air flow (initial pressure drop); filter life	raw material
JP 1007921 A 19890111	1989	Japan	MATSUSHITA DENKI SANGYO KK (MATU)	1	filter life	raw material
EP 325854 A 19890802	1989	EPO	3M CO (MINN)	3	filtration efficiency	raw material; composite of fibers or structure
EP 328419 A 19890816	1989	EPO	GIUSTI G (GIUS-I); HOSOKAWA MICRON INT (HOSO-N); HOSOKAWA MICRON INT INC (HOSO-N)	1	dust holding capacity	filtration device

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
EP 306277 A 19890308	1989	EPO	ITOMAN & CO LTD (ITOM-N); TABAI ESPEC CO LTD (TABA-N)	1	filtration efficiency	filtration device
DE 3731892 A 19890413	1989	Germany	SECO MASCHBAU GMBH (SECO-N)	3	filter life	filtration device
JP 1058314 A 19890306	1989	Japan	DAIDO TOKUSHUKO KK (DAIZ)	1	filtration efficiency	filtration device
WO 8909093 A 19891005	1989	WIPO	AMERICAN FILTRONA CORP (AMFI)	3	filtration efficiency; dust holding capacity; filter resistance to air flow (initial pressure drop); filter life; cost	filtration device; finishing
WO 8911156 A 19891116	1989	WIPO	TORAY IND INC (TORA); TORAY KK (TORA)	2	filtration efficiency	finishing
US 4824451 A 19890425	1989	USA	KIMBERLY CLARK CORP (KIMB)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	web formation and bonding
US 4917714 A 19900417	1990	USA	JAMES RIVER DIXIE NORTHERN INC (JAME)	2	energy costs/usage; improved manufacturing	composite of fibers or structure
WO 9013593 A 19901115	1990	WIPO	BRANCA P A (BRAN-I); DU PONT DE NEMOURS & CO E I (DUPO); GORE & ASSOC INC W L (GORE)	2	filtration efficiency	composite of fibers or structure
EP 391660 A 19901010	1990	EPO	GORE & ASSOC INC W L (GORE)	2	filtration efficiency	composite of fibers or structure
US 4917942 A 19900417	1990	USA	3M CO (MINN)	3	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
US 4904343 A 19900227	1990	USA	AMERICAN CYANAMID CO (AMCY)	1	filtration efficiency	composite of fibers or structure
JP 2233115 A 19900914	1990	Japan	ARISAWA MFG CO LTD (ARIA)	2	filter resistance to air flow (initial pressure drop)	raw material
EP 365111 A 19900425	1990	EPO	3M CO (MINN)	2	filtration efficiency	raw material
DE 3915248 A 19901115	1990	Germany	FESTO AG & CO (FSTM); FESTO KG (FSTM)	1	filtration efficiency	filtration device
EP 398847 A 19901122	1990	EPO	MARIANI F (MARI-I)	1	filtration efficiency	filtration device
WO 9009223 A 19900823	1990	WIPO	POLYSET CO (POLY-N); SILVERA R K (SILV-I)	2	filtration efficiency	filtration device; web formation and bonding
WO 9009837 A 19900907	1990	WIPO	AHLSTROM (AHLS)	2	improved manufacturing	web formation and bonding
US 4902423 A 19900220	1990	USA	GORE & ASSOC INC W L (GORE)	3	filtration efficiency; filter resistance to air flow (initial pressure drop)	web formation and bonding; raw material
JP 2119907 A 19900508	1990	Japan	SUZUKI SOHGYO KK (SUZU-N)	2	dust holding capacity	web formation and bonding; raw material
US 4904174 A 19900227	1990	USA	BATTELLE MEMORIAL INST (BATT); EXXON CHEM PATENTS INC (ESSO); MOOSMAYER P (MOOS-I)	2	filtration efficiency	web formation and bonding; finishing
WO 9108829 A 19910627	1991	WIPO	GORE & ASSOC INC W L (GORE); GORE & ASSOC W L (GORE)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
JP 3186309 A 19910814	1991	Japan	SHINAGAWA NENRYO KK (SHIZ); SHINANEN NEW CERAMIC KK (SHIN-N)	2	filter life	composite of fibers or structure
DE 3940264 A 19910613	1991	Germany	HOECHST AG (FARH)	2	filtration efficiency	composite of fibers or structure
HU 54531 T 19910328	1991	Hungary	DUDOK K (DUDO-I)	1		composite of fibers or structure
EP 408292 A 19910116	1991	EPO	FREUDENBERG FA CARL (FREU)	3	filtration efficiency	raw material
JP 3294342 A 19911225	1991	Japan	SUMITOMO CHEM CO LTD (SUMO)	2	filtration efficiency	raw material; finishing
US 5037455 A 19910806	1991	USA	GREAT AMER FILTER (GRAM-N)	2	filter resistance to air flow (initial pressure drop)	filtration device
JP 3109953 A 19910509	1991	Japan	MATSUSHITA DENKI SANGYO KK (MATU)	1	dust holding capacity	filtration device
US 5014608 A 19910514	1991	USA	BROD & MCCLUNG PACE (BROD-N)	1	filtration efficiency	filtration device
EP 443254 A 19910828	1991	EPO	SCOTT FETZER CO (SCOU)	2	filtration efficiency; dust holding capacity; filter resistance to air flow (initial pressure drop)	filtration device
JP 3056112 A 19910311	1991	Japan	HITACHI LTD (HITA)	1	filtration efficiency	filtration device
JP 3089910 A 19910415	1991	Japan	FUJITSU LID (FUIT); TORAY IND INC (TORA)	2	filtration efficiency; filter life	filtration device; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
WO 9111247 A 19910808	1991	WIPO	DE RUITER E (DRUI-I); TAKARA SHUZO CO LTD (TAKI); VON BLUCHER H (VBLU-I); VON BLUECHER H (VBLU-I)	2	filtration efficiency; filter life	filtration device; composite of fibers or structure
DE 4004343 A 19910814	1991	Germany	FISCHER-W FISCHER A (FISA)	2	improved manufacturing	web formation and bonding
US 5108474 A 19920428	1992	USA	GORE & ASSOC INC W L (GORE); GORE & ASSOC W L (GORE)	1	filtration efficiency; filter life; energy costs/usage	composite of fibers or structure
US 5096473 A 19920317	1992	USA	GORE & ASSOC INC W L (GORE)	1	filter life; energy costs/usage	composite of fibers or structure
AU 9184701 A 19920402	1992	Australia	PHILIP MORRIS LTD (PHIM)	1	dust holding capacity	composite of fibers or structure
US 5108470 A 19920428	1992	USA	PICK W (PICK-I)	2	filtration efficiency; dust holding capacity	composite of fibers or structure
JP 4161208 A 19920604	1992	Japan	TOYOBO KK (TOYM)	1	filtration efficiency	composite of fibers or structure
JP 4118012 A 19920420	1992	Japan	OHTSU TIRE & RUBBER CO LTD (OHTS)	1	filter resistance to air flow (initial pressure drop)	composite of fibers or structure
US 5082476 A 19920121	1992	USA	DONALDSON CO INC (DOND)	2	filtration efficiency; filter life	composite of fibers or structure
JP 4267918 A 19920924	1992	Japan	SONY CORP (SONY)	1	filtration efficiency	raw material; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
US 5114447 A 19920519	1992	USA	MOTT METALLURGICAL CORP (MOTM)	3	filtration efficiency; filter life	raw material; composite of fibers or structure
US 5102435 A 19920407	1992	USA	HAKO MINUTEMAN INC (HAKO-N); MINUTEMAN INT INC (MINU-N)	1		filtration device
GB 2252923 A 19920826	1992	UK	MERCEDES-BENZ AG (DAIM)	1	filtration efficiency; filter life	filtration device
JP 4247207 A 19920903	1992	Japan	FIUT (FIUT-N)	1	filtration efficiency	filtration device; composite of fibers or structure
JP 4176310 A 19920624	1992	Japan	MITSUI PETROCHEM IND CO LTD (MITC)	1	filtration efficiency	filtration device; composite of fibers or structure
EP 466381 A 19920115	1992	EPO	CHISSO CORP (CHCC)	3	filtration efficiency	filtration device; web formation and bonding
JP 4161209 A 19920604	1992	Japan	TOYOBO KK (TOYM)	2	filtration efficiency; dust holding capacity	filtration device; web formation and bonding; composite of fibers or structure
GB 2256601 A 19921216	1992	UK	DOMNICK HUNTER FILTERS LTD (DOMN-N); DOMNICK HUNTER LTD (DOMN-N)	1	filter life	finishing

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
WO 9201114 A 19920123	1992	WIPO	AHLSTROEM CORP A (AHLS)	2	filtration efficiency; filter life	web formation and bonding; composite of fibers or structure
JP 5295645 A 19931109	1993	Japan	TOYOBO KK (TOYM)	1	filtration efficiency	composite of fibers or structure
JP 5293318 A 19931109	1993	Japan	MORIMOTO T (MORI-I); SORYU KK (SORY-N)	2	filter life	composite of fibers or structure
DE 4304427 A1 19931021	1993	Germany	WEIDMANN AG H (WEID-N)	1		composite of fibers or structure
DE 4206442 A1 19930902	1993	Germany	HELSA WERKE SANDLER GMBH & CO (HELS-N)	1	filtration efficiency	composite of fibers or structure
JP 5057116 A 19930309	1993	Japan	ICHIKAWA KEORI KK (ICHW)	1	filter life	composite of fibers or structure
JP 5329363 A 19931214	1993	Japan	TAKENAKA KOMUTEN CO (TKEN)	1	filtration efficiency	composite of fibers or structure; finishing
EP 525630 A2 19930203	1993	EPO	DAIKIN IND LTD (DAIK); DAIKIN KOGYO KK (DAIK); TAMARU S (TAMA-I)	1	filtration efficiency; filter resistance to air flow (initial pressure drop)	raw material; composite of fibers or structure
WO 9313849 A1 19930722	1993	WIPO	DAIKIN IND LTD (DAIK); DAIKIN KOGYO KK (DAIK); OGANE CO LTD (OGAN-N)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	filtration device
DE 4208862 A1 19930923	1993	Germany	HENGST GMBH & CO KG WALTER (HENG-N)	1	improved manufacturing	filtration device

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
EP 547512 A1 19930623	1993	EPO	ELTECH SYSTEMS CORP (ELTE)	2	filtration efficiency	filtration device
WO 9323144 A1 19931125	1993	WIPO	SUMITOMO ELECTRIC IND CO (SUME)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	filtration device; composite of fibers or structure
JP 5245325 A 19930924	1993	Japan	MATSUSHITA DENKI SANGYO KK (MATU)	1	filtration efficiency	filtration device; composite of fibers or structure
JP 5096112 A 19930420	1993	Japan	MATSUSHITA DENKI SANGYO KK (MATU)	2	filter life	filtration device; composite of fibers or structure
JP 5293321 A 19931109	1993	Japan	HOKUETSU PAPER MILLS (HOKP); TOYOBO KK (TOYM)	2		filtration device; composite of fibers or structure
US 5273565 A 19931228	1993	USA	EXXON CHEM PATENTS INC (ESSO); UNIV TENNESSEE RES CORP (UYTE-N)	2	filter resistance to air flow (initial pressure drop)	web formation and bonding
JP 5253415 A 19931005	1993	Japan	MITSUI PETROCHEM IND CO LTD (MITC)	1	filtration efficiency	web formation and bonding
DE 4201288 A1 19930722	1993	Germany	DELBAG LUFTFILTER GMBH (DELB-N)	1	improved manufacturing	web formation and bonding
US 5230800 A 19930727	1993	USA	3M CO (MINN)	1	filtration efficiency	web formation and bonding; bonding; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
JP 5329314 A 19931214	1993	Japan	TOYOBO KK (TOYM)	2	filter life; improved manufacturing	web formation and bonding; composite of fibers or structure
US 5350443 A 19940927	1994	USA	DE RUITER E (DRUI-I); VON BLUECHER H (VBLU-I)	2	filtration efficiency; filter life	composite of fibers or structure
JP 6292809 A 19941021	1994	Japan	UNITIKA LTD (NIRA)	2	filtration efficiency	composite of fibers or structure
JP 6292808 A 19941021	1994	Japan	UNITIKA LTD (NIRA)	2	filtration efficiency	composite of fibers or structure
JP 6257049 A 19940913	1994	Japan	FREUDENBERG FA CARL (FREU)	1	filtration efficiency	composite of fibers or structure
JP 6254319 A 19940913	1994	Japan	TOYOBO KK (TOYM)	1	filtration efficiency	composite of fibers or structure
JP 6218231 A 19940809	1994	Japan	FREUDENBERG FA CARL (FREU)	1	filtration efficiency	composite of fibers or structure
DE 4239520 A1 19940526	1994	Germany	DE RUITER E (DRUI-I); VON BLUECHER H (VBLU-I)	2	filter life	composite of fibers or structure
US 5306321 A 19940426	1994	USA	DONALDSON CO INC (DOND)	1	filter life; energy costs/usage	composite of fibers or structure
JP 6047219 A 19940222	1994	Japan	TORAY IND INC (TORA)	1	filter resistance to air flow (initial pressure drop); filter life	composite of fibers or structure
EP 616831 A1 19940928	1994	EPO	3M CO (MINN)	3	filtration efficiency; filter resistance to air flow (initial pressure drop); filter life	composite of fibers or structure; finishing

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
EP 586924 A1 19940316	1994	EPO	KIMBERLY CLARK CORP (KIMB); KIMBERLY-CLARK CORP (KIMB); KIMBERLY-CLARK WORLDWIDE INC (KIMB)	2	improved manufacturing	raw material
JP 6055019 A 19940301	1994	Japan	FUJITSU LTD (FUIT); NITTA KK (NTTA)	2	filtration efficiency	raw material
US 5290330 A 19940301	1994	USA	ENVIRCO CORP (ENVI-N); UNIV JOHNS HOPKINS (UYJO)	2	filter life; energy costs/usage	filtration device
EP 630676 A1 19941228	1994	EPO	SUMITOMO ELECTRIC IND CO (SUME)	1	filtration efficiency; filter resistance to air flow (initial pressure drop)	filtration device
EP 593004 A1 19940420	1994	EPO	SCHWAEBISCHE HUETTENWERKE GMBH (SCHH)	1	filtration efficiency	filtration device
WO 9408779 A1 19940428	1994	WIPO	UNIV TENNESSEE (UYTE-N); UNIV TENNESSEE RES CORP (UYTE-N)	3	filtration efficiency	finishing
JP 6346353 A 19941220	1994	Japan	TONEN KAGAKU KK (TOFU)	2	filtration efficiency	web formation and bonding

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
EP 594123 A1 19940427	1994	EPO	MITSUI Group; MITSUI PETROCHEM IND CO LTD (MITC); MITSUI PETROCHEMICAL IND LTD (MITC); MITSUI PETROLEUM CHEM IND CO LTD (MITC)	2	filtration efficiency; dust holding capacity; filter life	web formation and bonding; raw material; composite of fibers or structure
US 5419953 A 19950530	1995	USA	CHAPMAN R L (CHAP-I)	1	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
WO 9519828 A1 19950727	1995	WIPO	EXTRACTION SYSTEMS INC (EXTR-N)	2	filtration efficiency	composite of fibers or structure
WO 9517946 A1 19950706	1995	WIPO	COROVIN GMBH (CORO-N); KALTHOFF LUFTFILTER & FILTERMEDIEN GMBH (KALT-N)	2	filtration efficiency; filter life	composite of fibers or structure
JP 7112104 A 19950502	1995	Japan	TOYOBO KK (TOYM)	1	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
RU 2035969 C1 19950527	1995	Russian Federation	SEREBRYANSK INORG PRODN WKS (SERE-R)	1	dust holding capacity	composite of fibers or structure
WO 9518265 A1 19950706	1995	WIPO	LITTLE RAPIDS CORP (LITT-N)	2		composite of fibers or structure
JP 7136502 A 19950530	1995	Japan	OSAKA GAS CO LTD (OSAG)	1	filtration efficiency	composite of fibers or structure
EP 656224 A1 19950607	1995	EPO	PAPCEL PAPIER & CELLULOSE TECHNOLOGIE (PAPC-N)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure

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Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
DE 4331587 A1 19950323	1995	Germany	DE RUITER E (DRUI-I); VON BLUECHER H (VBLU-I)	1	improved manufacturing	composite of fibers or structure
JP 7016411 A 19950120	1995	Japan	KUREHA CHEM IND CO LTD (KURE)	2	filter resistance to air flow (initial pressure drop)	composite of fibers or structure
JP 7097758 A 19950411	1995	Japan	NIPPON PETROCHEMICALS CO LTD (NIPE)	1	filter life	composite of fibers or structure
WO 9505501 A2 19950223	1995	WIPO	3M CO (MINN); MINNESOTA MINING&MFG CO (MINN)	3	filtration efficiency	composite of fibers or structure; finishing
EP 673667 A2 19950927	1995	EPO	ASAHI KOGAKU KOGYO KK (ASAO); FUJIMI SHOUKAI YG (FJMI); FUJIMI SHOUKAI YK (FJMI)	1	filtration efficiency	raw material; composite of fibers or structure
WO 9534366 A1 19951221	1995	WIPO	APPLIANCE DEV CORP (APPL-N)	2	filtration efficiency	filtration device
WO 9504587 A1 19950216	1995	WIPO	BAPTISTA F A (BAPT-I); PEREIRA DIAS BAPTISTA J M (BAPT-I)	2	filtration efficiency	filtration device
DE 19508427 A1 19951109	1995	Germany	BRANOFILTER GMBH (BRAN-N)	1	dust holding capacity	filtration device
JP 7204536 A 19950808	1995	Japan	KAJIMA CORP (KAJI)	1	filtration efficiency	filtration device
JP 7060031 A 19950307	1995	Japan	OMORI KK (OMOR-N)	1		filtration device
WO 9533570 A1 19951214	1995	WIPO	COPPOM R (COPP-I); COPPOM R R (COPP-I); COPPOM TECHNOLOGIES (COPP-N)	2	filtration efficiency; filter resistance to air flow (initial pressure drop); filter life	filtration device; finishing

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
US 5397632 A 19950314	1995	USA	REEMAY INC (REEM-N)	1	filter life	finishing
JP 7313821 A 19951205	1995	Japan	MITSUI PETROCHEM IND CO LTD (MITC)	1	improved manufacturing	web formation and bonding
JP 8224414 A 19960903	1996	Japan	SANYO ELECTRIC CO LTD (SAOL)	1		composite of fibers or structure
JP 8252414 A 19961001	1996	Japan	NITTA KK (NTTA)	1	improved manufacturing	composite of fibers or structure
DE 29509282 U1 19961010	1996	Germany	VIVELLE GMBH (VIVE-N)	1	filter life; improved manufacturing	composite of fibers or structure
AT 9501674 A 19960715	1996	Austria	EICHENAUER T (EICH-I)	1	filtration efficiency; filter life	composite of fibers or structure
JP 8117576 A 19960514	1996	Japan	TOKUYAMA SODA KK (TOKU)	2	filtration efficiency	composite of fibers or structure
WO 9614136 A1 19960517	1996	WIPO	GORE & ASSOC INC W L (GORE); GORE & ASSOC W L (GORE)	3	filtration efficiency	composite of fibers or structure
JP 8010540 A 19960116	1996	Japan	TOYOBO KK (TOYM)	1	filtration efficiency	composite of fibers or structure
DE 4429165 A1 19960222	1996	Germany	HOECHST AG (FARH); TICONA GMBH (TICO-N)	2	filtration efficiency	raw material
US 5496627 A 19960305	1996	USA	EASTMAN CHEM CO (EACH)	3	filtration efficiency	raw material; composite of fibers or structure
WO 9604063 A1 19960215	1996	WIPO	GORE & ASSOC INC W L (GORE)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	raw material; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
WO 9637276 A1 19961128	1996	WIPO	COHEN B (COHE-I); KIMBERLY CLARK CORP (KIMB); KIMBERLY-CLARK CORP (KIMB); KIMBERLY-CLARK WORLDWIDE INC (KIMB)	2	filtration efficiency	raw material; finishing
DE 19517197 A1 19961114	1996	Germany	BUTSCH M (BUTS-I)	2	filtration efficiency	filtration device
JP 8033856 A 19960206	1996	Japan	FREUDENBERG FA CARL (FREU)	2	filtration efficiency	filtration device; composite of fibers or structure
JP 8047614 A 19960220	1996	Japan	NIPPONDENSO CO LTD (NPDE)	2		filtration device; web formation and bonding
US 5496507 A 19960305	1996	USA	3M CO (MINN)	3	filtration efficiency	web formation and bonding
JP 8309124 A 19961126	1996	Japan	TOYOBO KK (TOYM)	1	filtration efficiency	web formation and bonding
JP 8144166 A 19960604	1996	Japan	TOYOBO KK (TOYM)	2	filtration efficiency	web formation and bonding
US 5582865 A 19961210	1996	USA	EXTRACTION SYSTEMS INC (EXTR-N)	1	filtration efficiency; filter resistance to air flow (initial pressure drop)	web formation and bonding; composite of fibers or structure
US 5569489 A 19961029	1996	USA	KASMARK J W (KASM-I)	3	filtration efficiency; filter life	web formation and bonding; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
WO 9600807 A1 19960111	1996	WIPO	DAIKIN IND LTD (DAIK)	3	filtration efficiency	web formation and bonding; raw material
US 5634954 A 19970603	1997	USA	SCHULLER INT INC (SCHU-N)	1	dust holding capacity; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
US 5609947 A 19970311	1997	USA	TONEN CHEM CORP (TOFU)	2	filtration efficiency; filter life	composite of fibers or structure
WO 9737745 A1 19971016	1997	WIPO	SHELL OIL CO (SHEL)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
WO 9736667 A1 19971009	1997	WIPO	SORRICK C H (SORR-I)	2	filtration efficiency; filter life	composite of fibers or structure
WO 9723267 A1 19970703	1997	WIPO	KIMBERLY CLARK CORP (KIMB); KIMBERLY-CLARK CORP (KIMB); KIMBERLY-CLARK WORLDWIDE INC (KIMB); PIKE R D (PIKE-I); SHIPP P W (SHIP-I)	2	filtration efficiency; filter resistance to air flow (initial pressure drop); filter life	composite of fibers or structure
US 5672399 A 19970930	1997	USA	DONALDSON CO INC (DOND)	2	filtration efficiency; filter life	composite of fibers or structure
DE 19533464 A1 19970313	1997	Germany	DE RUITER E (DRUI-I); VON BLUECHER H (VBLU-I)	1	dust holding capacity	composite of fibers or structure
WO 9700347 A2 19970103	1997	WIPO	PALL CORP (PALL)	3	filtration efficiency	composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
DE 19521680 A1 19970109	1997	Germany	DE RUITER E (DRUI-I); VON BLUECHER H (VBLU-I)	2		composite of fibers or structure
WO 9744509 A1 19971127	1997	WIPO	KIMBERLY-CLARK CORP (KIMB); KIMBERLY-CLARK WORLDWIDE INC (KIMB)	3	filtration efficiency	raw material
WO 9739817 A1 19971030	1997	WIPO	KIMBERLY-CLARK WORLDWIDE INC (KIMB)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	raw material; composite of fibers or structure
WO 9745189 A1 19971204	1997	WIPO	PHILIPS ELECTRONICS NV (PHIG); PHILIPS NORDEN AB (PHIG); US PHILIPS CORP (PHIG)	1	filtration efficiency	filtration device
US 5678576 A 19971021	1997	USA	GADGIL A J (GADG-I); NAZAROFF W W (NAZA-I)	1	filtration efficiency	filtration device
US 5626820 A 19970506	1997	USA	HIGLEY J K (HIGL-I); KINKEAD D A (KINK-I); REZUKE R W (REZU-I)	2	filtration efficiency	filtration device
US 5593476 A 19970114	1997	USA	COPPOM TECHNOLOGIES (COPP-N)	2	filtration efficiency; dust holding capacity; energy costs/usage	filtration device
JP 9317438 A 19971209	1997	Japan	HINO MOTORS LTD (HINM)	1	filter life	filtration device
DE 19528670 A1 19970206	1997	Germany	FREUDENBERG FA CARL (FREU)	2	improved manufacturing	filtration device

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
US 5607735 A 19970304	1997	USA	KIMBERLY CLARK CORP (KIMB); KIMBERLY CLARK WORLDWIDE INC (KIMB); KIMBERLY-CLARK WORLDWIDE INC (KIMB)	1	filtration efficiency	filtration device; composite of fibers or structure
WO 9730772 A1 19970828	1997	WIPO	VORWERK & CO INTERHOLDING GMBH (VORW)	1	filter life	filtration device; composite of fibers or structure
TW 305753 A 19970521	1997	Taiwan	REYNOLDS TOBACCO CO R J (RETO)	2	filter resistance to air flow (initial pressure drop)	filtration device; composite of fibers or structure
WO 9740913 A1 19971106	1997	WIPO	3M CO (MINN); RACAL CORP CANADA INC (RACA)	2		web formation and bonding; composite of fibers or structure
WO 9730771 A1 19970828	1997	WIPO	3M CO (MINN); HASKETT T E (HASK-I)	2	dust holding capacity; filter resistance to air flow (initial pressure drop)	web formation and bonding; composite of fibers or structure
JP 10192705 A 19980728	1998	Japan	NISSO ENG KK (NIRS)	1	filtration efficiency	composite of fibers or structure
WO 9831547 A1 19980723	1998	WIPO	GORE ENTERPRISE HOLDINGS INC (GORE)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
EP 850692 A1 19980701	1998	EPO	KOKEN KK (KOKE)	2	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
JP 10287759 A 19981027	1998	Japan	NITTO DENKO CORP (NITL)	1	filtration efficiency; dust holding capacity	composite of fibers or structure
US 5820645 A 19981013	1998	USA	REEMAY INC (REEM-N)	2	filter life	composite of fibers or structure
JP 10234835 A 19980908	1998	Japan	TOSHIBA AVE KK (TOSA); TOSHIBA KK (TOKE)	2	filtration efficiency	composite of fibers or structure
DE 19708692 A1 19980917	1998	Germany	BLUECHER GMBH (BLUE-N); MHB FILTRATION GMBH & CO KG (MHBF-N)	1	dust holding capacity; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
JP 10180023 A 19980707	1998	Japan	KUREHA TEC KK (KURE-N); NIPPONDENSO CO LTD (NPDE); TOYOTA JIDOSHA KK (TOYT)	1		composite of fibers or structure
JP 10085526 A 19980407	1998	Japan	KUREHA TEC KK (KURE-N); NIPPONDENSO CO LTD (NPDE); TOYOTA JIDOSHA KK (TOYT)	1	dust holding capacity; filter life	composite of fibers or structure
US 5728187 A 19980317	1998	USA	SCHULLER INT INC (SCHU-N)	2	filter resistance to air flow (initial pressure drop)	composite of fibers or structure
JP 10066814 A 19980310	1998	Japan	BABCOCK-HITACHI KK (HITG)	1	filtration efficiency	raw material
WO 9823358 A1 19980604	1998	WIPO	ALLIED-SIGNAL INC (ALLC); HONEYWELL INT INC (HONE)	3	filtration efficiency	raw material

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
JP 10033921 A 19980210	1998	Japan	SEKISUI PLASTICS CO LTD (SEKP)	1		raw material
WO 9804334 A1 19980205	1998	WIPO	NIKKI UNIVERSAL CO LTD (NIKK-N)	3	filtration efficiency	raw material
WO 9806476 A1 19980219	1998	WIPO	DAIKIN IND LTD (DAIK); DAIKIN KOGYO KK (DAIK)	1	filter life	raw material; composite of fibers or structure
JP 10311550 A 19981124	1998	Japan	MATSUSHITA DENKI SANGYO KK (MATU)	1	filtration efficiency	filtration device
JP 2810983 B2 19981015	1998	Japan	HIRAYAMA T (HIRA-I)	2	filtration efficiency	filtration device
US 5761908 A 19980609	1998	USA	AIR QUALITY ENG (AIRQ-N)	2	filtration efficiency	filtration device
US 5730766 A 19980324	1998	USA	BHA GROUP INC (BHAB-N)	2	filtration efficiency	filtration device
JP 10000316 A 19980106	1998	Japan	KAWASAKI STEEL CORP (KAWI)	1		filtration device
JP 10277334 A 19981020	1998	Japan	KUMA C (KUMA-I); NISHIBU GIKEN KK (NISH-N)	1	dust holding capacity; filter resistance to air flow (initial pressure drop)	filtration device
GB 2321604 A 19980805	1998	UK	SMITHS IND PLC (SMIS)	1		filtration device
JP 10128019 A 19980519	1998	Japan	INOAC CORP KK (INOA-N)	1	improved manufacturing	filtration device
JP 10118470 A 19980512	1998	Japan	MITSUBISHI	1		finishing
JP 10099622 A 19980421	1998	Japan	AGENCY OF IND SCI & TECHNOLOGY (AGEN); DOKURITSU GYOSEI HOJIN SANGYO GIJUTSU SO (NIIT); NGK SPARK PLUG CO LTD (NITS)	2	filtration efficiency; filter life	finishing

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
JP 10212683 A 19980811	1998	Japan	OWA SEISHI KK (OWAS-N); TSUCHIYA SEISAKUSHO KK (TSUA)	2	improved manufacturing	web formation and bonding
JP 10309417 A 19981124	1998	Japan	BESTEX KK (BEST-N)	2	filtration efficiency	web formation and bonding; composite of fibers or structure
WO 9811974 A1 19980326	1998	WIPO	BLADON INT INC (BLAD-N)	2	improved manufacturing	web formation and bonding; raw material
US 5993501 A 19991130	1999	USA	JOHNS MANVILLE INT INC (JOHM)	2	dust holding capacity; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
US 5900305 A 19990504	1999	USA	CHAPMAN R L (CHAP-I)	3	filtration efficiency; dust holding capacity	composite of fibers or structure
WO 9958041 A2 19991118	1999	WIPO	AIRFLI EURO NV (AIRF-N); SYNSORB BIOTECH INC (SYNS-N)	1	filtration efficiency; filter resistance to air flow (initial pressure drop); filter life	composite of fibers or structure
GB 2335379 A 19990922	1999	UK	UPF CORP (UPFU-N)	1	filter resistance to air flow (initial pressure drop); filter life	composite of fibers or structure
JP 11188212 A 19990713	1999	Japan	NEC YAMAGATA LTD (NIDE); TAKUMA KK (TAKU)	1	filtration efficiency	composite of fibers or structure
JP 11047521 A 19990223	1999	Japan	TOYOBO KK (TOYM)	1	dust holding capacity; filter life	composite of fibers or structure
JP 11333234 A 19991207	1999	Japan	DYNIC CORP (DYNI)	1		composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
JP 11226329 A 19990824	1999	Japan	OJI PAPER CO (OJIP)	1	filter life	composite of fibers or structure
JP 11104415 A 19990420	1999	Japan	YAMAZAKI S (YAMA-I)	1	filtration efficiency	composite of fibers or structure
JP 11104414 A 19990420	1999	Japan	HAGIWARA KOGYO KK (HAGI-N); YAMAZAKI S (YAMA-I)	1	filtration efficiency; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
JP 11076732 A 19990323	1999	Japan	OSAKA GAS CO LTD (OSAG)	1	filtration efficiency	composite of fibers or structure
US 5874373 A 19990223	1999	USA	AMERICAN FELT & FILTER CO (AMFE-N)	2	filtration efficiency; dust holding capacity	composite of fibers or structure
JP 11028324 A 19990202	1999	Japan	DUSKIN CO LTD (DUSK)	1		composite of fibers or structure
EP 923983 A1 19990623	1999	EPO	NGK INSULATORS LTD (NIGA)	1	filtration efficiency; filter life	raw material
WO 9958224 A1 19991118	1999	WIPO	TEXEL INC (TEXE-N)	2	filtration efficiency; dust holding capacity; filter resistance to air flow (initial pressure drop)	raw material
EP 962244 A1 19991208	1999	EPO	MITSUBISHI PLASTICS INC (MISD)	1	filter life	raw material
JP 11156345 A 19990615	1999	Japan	TOKYO YOGYO KK (TOLY)	1		raw material
JP 11070305 A 19990316	1999	Japan	TOKUSHU SEISHI KK (TOSD)	1		raw material
DE 19805011 A1 19990812	1999	Germany	BEHR GMBH & CO (BHRT)	2	dust holding capacity; filter resistance to air flow (initial pressure drop)	raw material; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
DE 29915434 U1 19991230	1999	Germany	EISMANN F (EISM-I); STOEBE P (STOE-I)	1		raw material; composite of fibers or structure
EP 920897 A1 19990609	1999	EPO	NIPPON AIR FILTER KK (NIAI-N); TODA KOGYO CORP (TODA); TODA KOGYO KK (TODA); YOSHIDA H (YOSH-I)	1	filtration efficiency	raw material; finishing
WO 9916945 A1 19990408	1999	WIPO	3M CO (MINN)	2	dust holding capacity	raw material; finishing
US 5997619 A 19991207	1999	USA	NQ ENVIRONMENTAL INC (NQEN-N)	2	filtration efficiency	filtration device
JP 11300141 A 19991102	1999	Japan	KOGANEI KK (KOGA-N)	1	filtration efficiency	filtration device
JP 11221442 A 19990817	1999	Japan	SHARP KK (SHAF)	1	filtration efficiency	filtration device
WO 9938602 A1 19990805	1999	WIPO	CHAHAL K (CHAH-I)	1	filter life	filtration device
JP 11169634 A 19990629	1999	Japan	MITSUBISHI ELECTRIC CORP (MITQ)	1	dust holding capacity	filtration device
US 5984990 A 19991116	1999	USA	MCDONALD K (MCDO-I)	1	filtration efficiency	filtration device
JP 11285462 A 19991019	1999	Japan	KOWA CO LTD (KOWA); MORUZA KK (MORU-N)	1		filtration device
JP 11267436 A 19991005	1999	Japan	TOKYO KOKI KK (TOKK-N)	1		filtration device
US 5972059 A 19991026	1999	USA	FARR CO (FARR-N)	2	filtration efficiency	filtration device
JP 11192405 A 19990721	1999	Japan	SANKI KOGYO KK (SAOF)	1	filtration efficiency	filtration device
JP 11182922 A 19990706	1999	Japan	RF YAMAKAWA KK (RFYA-N)	1	energy costs/usage	filtration device

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
JP 11179125 A 19990706	1999	Japan	NITTA KK (NTTA)	1	filter life	filtration device
JP 11019435 A 19990126	1999	Japan	TONEN TAPIRUSU KK (TONE-N)	2	filtration efficiency	filtration device; web formation and bonding
JP 2000153122 A 20000606	2000	Japan	KYOSEI SANGYO KK (KYOS); MINE SAFETY APPLIANCES CO (MINJ); MSA JAPAN KK (MINJ); TONEN TAPIRUSU KK (TONE-N)	1	dust holding capacity; filter resistance to air flow (initial pressure drop)	composite of fibers or structure
JP 2000033244 A 20000202	2000	Japan	DAIKIN KOGYO KK (DAIK)	1	filtration efficiency	composite of fibers or structure
WO 200062899 A1 20001026	2000	WIPO	FILTERWERK MANN & HUMMEL GMBH (FILW); KLEIN G (KLEI-I)	1	filter life	composite of fibers or structure
DE 20010049 U1 20000914	2000	Germany	AICHNER FILTER GMBH (AICH-N)	1	dust holding capacity; filter life	composite of fibers or structure
JP 2000210511 A 20000802	2000	Japan	MITSUBISHI	1	filtration efficiency	composite of fibers or structure
JP 2000140587 A 20000523	2000	Japan	MSA JAPAN KK (MINJ); TONEN TAPIRUSU KK (TONE-N)	1	filter resistance to air flow (initial pressure drop)	composite of fibers or structure
US 6036739 A 20000314	2000	USA	NEW C W (NEWC-I)	2	filter resistance to air flow (initial pressure drop)	composite of fibers or structure
EP 1010673 A2 20000621	2000	EPO	CLOCKSIN K A (CLOC-I); CUSICK M J (CUSI-I); JOHNS MANVILLE INT INC (JOHM)	3	improved manufacturing	raw material

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
WO 200037160 A1 20000629	2000	WIPO	CAMBRIDGE FILTER JAPAN LTD (CAMB-N); KONDO KOGYO KK (KOND-N); KONDOH IND LTD (KOND-N); NIPPON CAMBRIDGE FILTER KK (NICA-N); TAISEI CONSTR CO LTD (TAKJ); TAISEI KENSETSU KK (TAKJ)	2	filtration efficiency	raw material
JP 2000169254 A 20000620	2000	Japan	KYOCERA CORP (KYOC)	1	filter life	raw material
WO 200025610 A1 20000511	2000	WIPO	PHILIP MORRIS INC (PHIM); PHILIP MORRIS PROD INC (PHIM); PHILIP MORRIS USA INC (PHIM)	3	filtration efficiency	raw material
WO 200003785 A1 20000127	2000	WIPO	DU PONT DE NEMOURS & CO E I (DUPO)	2	filtration efficiency	raw material; composite of fibers or structure
EP 1050331 A1 20001108	2000	EPO	FIBERMARK GESSNER GMBH & CO (FIBE-N); FIBERMARK GESSNER GMBH & CO OHG (FIBE-N); NEENAH GESSNER GMBH (NEEN-N)	2	filter life	raw material; composite of fibers or structure
EP 980700 A2 20000223	2000	EPO	JOHNS MANVILLE INT INC (JOHM)	2	filtration efficiency	raw material; composite of fibers or structure

Table 51 continued

Basic Patent Number	Basic Patent Year	Basic Patent Country	Patent Assignees	LOI	Performance Improvements	System element
WO 200000267 A2 20000106	2000	WIPO	KIMBERLY-CLARK WORLDWIDE INC (KIMB); LASSIG J J (LASS-I); MIDKIFF D G (MIDK-I); MYERS D L (MYER-I); TURKEVICH L A (TURK-I)	3	filtration efficiency	raw material; composite of fibers or structure
US 6136057 A 20001024	2000	USA	DANG A (DANG-I); REDFURN L (REDF-I)	1	energy costs/usage	filtration device
JP 2000081231 A 20000321	2000	Japan	TECHNO RYOWA KK (TECH-N)	1	energy costs/usage	filtration device
US 6036757 A 20000314	2000	USA	HONEYWELL INC (HONE)	2	energy costs/usage	filtration device
WO 200059604 A1 20001012	2000	WIPO	ANDREAE FILTERS INC (ANDR-N)	1	improved manufacturing	filtration device
US 6080218 A 20000627	2000	USA	PIRKLE S (PIRK-I)	1	filtration efficiency	filtration device
WO 200023172 A1 20000427	2000	WIPO	AIR-MAZE CORP (AIRM-N)	1	improved manufacturing	filtration device
JP 2000218112 A 20000808	2000	Japan	MATSUSHITA DENKI SANGYO KK (MATU)	2	filtration efficiency	filtration device; composite of fibers or structure

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