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Forecasting emerging technologies: Use of bibliometrics and patent analysis

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Abstract

It is rather difficult to forecast emerging technologies as there is no historical data available. In such cases, the use of bibliometrics and patent analysis have provided useful data. This paper presents the forecasts for three emerging technology areas by integrating the use of bibliometrics and patent analysis into well-known technology forecasting tools such as scenario planning, growth curves and analogies. System dynamics is also used to be able to model the dynamic ecosystem of the technologies and their diffusion. Technologies being forecasted are *fuel cell, food safety and optical storage* technologies. Results from these three applications help us to validate the proposed methods as appropriate tools to forecast emerging technologies.

1. Introduction

Technology forecasting experts agree that models should be used in combination [1,2]. With complex consumer technologies there are usually several organization factors—political, cultural, etc—that influence the rate of diffusion for a commercial technology. Technical trend analyses alone usually cannot incorporate the organizational and political scenarios that will influence future technologies. The analysis proposed for the models incorporates several different technology forecasting methodologies spanning the technical, organizational personal perspectives (see Fig. 1) [3]. Technical perspectives are addressed using data for historical analogies as well as patent trend analysis curve fitting. Organizational influences

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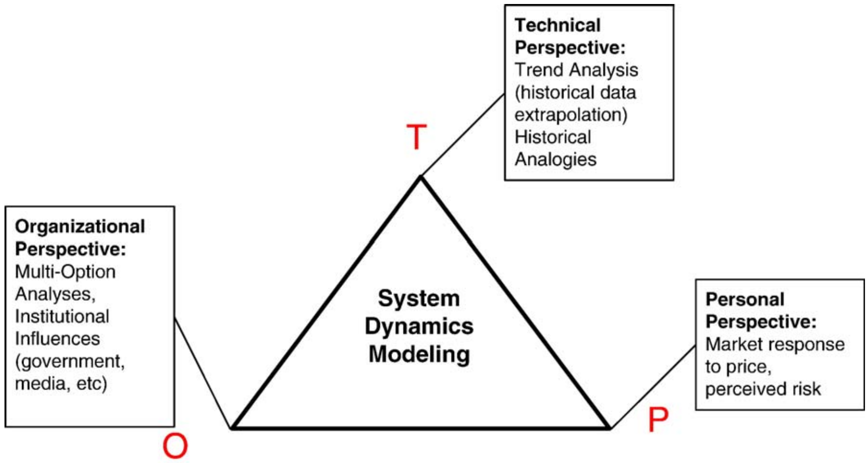


Fig. 1. Methodology incorporating Linstone's multiple perspectives [3,4].

are incorporated using scenarios for possible government or media influence and the personal perspective is incorporated by calibrating variables to represent consumer preferences. System dynamics incorporates all these variables in a numeric model representing complex feedback loops and generating projected S-curves representing market penetration.

Traditional system dynamic models used in technology forecasting incorporate historical data for calibration and validation. Models here also integrate the use of scenarios, bibliometrics, and patent trend analysis. System dynamics models have typically not been viewed as appropriate forecasting tools but are used primarily to uncover feedback loops and how factors interrelate for strategic analysis [1]. By incorporating scenario planning and the use of bibliometrics, patent analysis and growth curve model it is our belief that these models can also become a useful decision-making tool.

The organization of this paper is as follows. A review of the main methodologies used in the applications is presented in the literature review in Section 2. This is followed by a brief description of the methodology and model details for each application in Section 3. Finally the conclusions and future work are presented in Section 4.

2. Literature review

Mishra et al. [5] studied appropriateness of technology forecasting for different kinds of technologies. Although they provide a very comprehensive methodology to pick the right method, many methods are limited in terms of comprehending the whole ecosystem when forecasting emerging technologies. For that reason, we propose the use of multiple methods. Meade et al [6] also reviewed available technology forecasting models and they also recommend the combination of model forecasts.

Porter et al. [7] provides a comprehensive review of available methods in terms of parameters being forecasted. We use methods from each category to comprehend the ecosystem and conclude that forecasts for emerging technologies need to include methods from all three categories (Table 1).

In this section we will review methodologies used in our applications.

Table 1
Technological forecasting methods by [7]

Category	Definition	Forecasting Methods
Direct	Direct forecast of parameter(s) that measure an aspect of this technology	Expert Opinion (Delphi, Surveys, NG), time series analysis, trend extrapolation (growth curves, substitution, life cycle)
Correlative	Correlative parameter(s) that measure the technology with parameters or other technologies	Scenarios, lead–lag indicators, cross impact, technology progress function, analogy
Structural	Explicit consideration of cause-and-effect relationships that effect growth	Causal models, regression analysis, simulation models (deterministic, stochastic, gaming), relevance trees, morphology

2.1. Patent analysis

Patents are useful for competitive analysis and technology trend analysis [8,9]. Patents have always been analyzed in R and D project management to assess competitive position and to avoid infringement. Patent analysis is also a valuable approach that uses patent data to derive information about a particular industry or technology used in forecasting. Patent growth generally follows a similar trend that can resemble s-shaped growth. In early stages of a technology the number of patents issued is very limited. A fast-growing period then follows when the number of patents filed and issued increases and then a plateau is reached [8]. Because the patent process is costly and can take several years, filing a patent generally means there is optimism in economic or technical contribution [10].

Several indices have been introduced to measure technological strength as a function of patent quantity or patent quality. Some examples include patent citation indices and regression models [8,11,12]. Because the total number of patents over time for a technology has a saturation point, using growth curves can also be useful [13]. Other models aim to describe the relationship between patents using citation networks [14].

Patent analysis has been shown to be valuable in planning technology development from the analysis of strategy at a national level [9] to modeling specific emerging technologies [15,13,8]. Patent data is usually freely accessible in most countries and several guidelines have been introduced to enhance the technique using keywords and categorization.

Much like text and journal information, very few patents actually develop into something of commercial value however most are technically significant because they encourage or lead to follow-on developments in technology [15]. Understanding the growth in an area of technology and measuring using keywords or phrases can be an insightful to an overall technology forecasting model.

2.2. Bibliometric analysis

Bibliometrics is defined by Norton [16] as the measurement of texts and information. Historically bibliometric methods have been used to trace back academic journal citations. However, today bibliometrics can be used to understand the past and even potentially to forecast the future [17]. Bibliometrics helps to explore, organize and analyze large amounts of historical data helping researchers to identify “hidden patterns” that may help researchers in the decision making process. Some common tools that have been used in bibliometrics have been authors, affiliations, conceptual maps, cluster and factor analysis, citation and co-citation analysis to mention some of them.

Important works have been presented by Morris et al. [17] using a Database Information Visualization and Analysis system called DIVA where documents are visualized as clusters on a two dimensional map. Kostoff et al. [18] present database tomography for textual database analysis extracting multiword phrase frequencies and determining phrase proximities using Science Citation Index (SCI) and the Engineering Compendex (EC) databases. Bibliometric analysis helps to identify the recent most prolific topical area authors; the journals that contain numerous topical area papers; the institutions that produce numerous topical area papers; the keywords specified most frequently by the topical area authors and the authors whose work is cited most frequently. Also, Porter and Watts [19–22] have presented relevant papers in data-mining using a proprietary software called the VantagePoint. Porter used a combination of bibliometrics with other forms of technological evidence naming it as *innovation forecasting*.

Porter [21,22] and Pilkington [23,24] presented bibliometric applications for the engineering and technology management field. Both study how bibliometrics helps to identify hidden patterns classifying information by authors, organizations, countries, collaborations, co-citations, and so on.

2.3. System dynamics

System Dynamics (SD) is an approach to modeling the dynamics of complex systems. SD was founded in the early 60s by Jay W. Forrester [25]. They are highly recommended in dealing with complex problems, strategy and policy decisions, models with unintended side-effects, delay times involved and problems which have failed prior attempts to solve [26,27]. Much of the system dynamics concepts are generated using basic concepts such as feedback, time delays, and non-linearity effects determining the dynamics of a system. All dynamics come up from the multiple interaction of two types of feedback loops, positive or reinforcing and negative or balancing. Positive loops amplify the behavior of the system while negative loops counteract and oppose change.

However system dynamics do not always work in simple structures. Dynamics are much more complex when there are multiple loop systems wherein results are not always obvious to determine unless simulation is done (see Fig. 2).

What makes System Dynamics different from other approaches is the use of feedback loops creating non-linear behaviors. A feedback loop is described as the output of the system influencing the input to the system. Sterman [27] concluded that the observed dysfunction in dynamics arises from what he called *misperceptions of feedback* due to the dynamic deficiency of the models used by people. People commonly adopt an *open-loop view of causality, ignoring feedback processes* and *delay times*, and most important they are commonly unconscious to the effects of *non-linearities*. Non-linear systems mean that

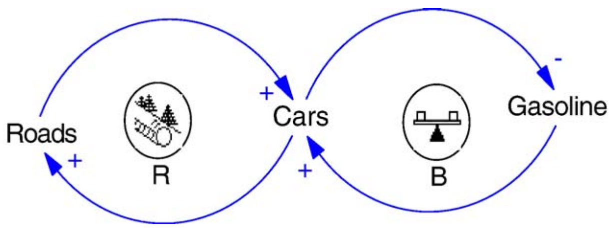


Fig. 2. Balancing and reinforcing loops combine.

effects from inputs operating separately are completely different than the sum of inputs operating together. In other words, non-linear systems do not fulfill the principle of superposition.

Some interesting applications in the system dynamics applied to forecast are presented in the works of Kabir et al. [28] and Warr and Ayres [29]. Kabir presented system dynamics modeling for forecasting technological substitution which he called the *multilevel substitution process*. The developed model makes forecast of the market share as well as the actual size of the market for each of the competing technologies. Warr and Ayres presented a forecasting model for assessing the impact of natural resource consumption and technological change on economic growth. Their model simulated the economic growth of the US through the 20th century and extrapolates the simulation for several decades into the next century. The model generated endogenous data for the dynamics of technological change.

2.4. Growth curves

Growth curves represent the growths in performance over time. They were created making analogy to the growth of a living organism [30,31]. Growth curves are frequently used to forecast the substitution of one technology for another [2].

Table 2 shows some of the most common transformation for technological growth curves described by [7].

The Gompertz model assumptions are different and this model is often referred to as the *"mortality model"* in technology forecasting. The Gompertz model produces an S-curve which rises more sharply but begins to taper off earlier than the Fisher–Pry model [7]. The Fisher–Pry model predicts characteristics very similar to those of biological system growth. This is the reason that it is commonly referred to as the *"substitution model"* based on its application in forecasting in which the rate of new technology will replace existent technology. The Fisher–Pry presents a slow beginning, a rapid slope and a tapering off at the finish. Fig. 3 presents the comparison between the Fisher–Pry and the Gompertz models for the cable television in the U.S.

Another type of growth curve is the Voltera–Lotka built upon the predator–prey relationship [7], which have helped long range forecasts by providing tools to forecast two competing technologies in a market. It was even used by Motis [32] to forecast the stock market.

2.5. Scenarios

Scenarios are used to outline of some aspects of the future world by telling stories to emphasize the important dimensions and incorporate uncertainty. Scenarios are used in areas such as analysis of US energy scenarios [33], the future of hydrogen fueling systems [34] and biotechnology [35]. Scenarios may

Table 2
Typical growth models [7]

Growth model	Transformation
Exponential	$Z = \log_{10} Y$(or ln Y)
Pearl (Fisher–Pry, single variable)	$Z = \ln[(L - Y)/Y]$ where L is the upper growth limit
Gompertz	$Z = \ln[\ln(L/Y)]$
Substitution	$Z = \ln[f(1-f)]$ where L is the upper growth limit and f is the fraction of the market held by the new technology.

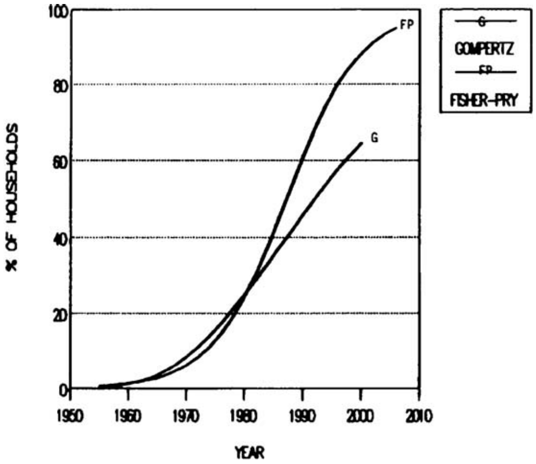


Fig. 3. Fisher–Pry versus Gompertz models for cable television subscribers in the U.S. [7].

be future histories that may cover dynamic time trajectory from the present to some point in the future or snapshots that may be a structural cross-section at a single time point in the future or combinations of both. [7]. Scenarios are used in forecasting, policy, and planning processes as well as in business and government applications.

3. Applications

This section will review three applications to demonstrate the use of multiple methods to forecast emerging technologies. Figs. 4–6 describe the general process followed for each application and how similar tools have been applied to determine fuel cell, food safety and optical storage market future. In the

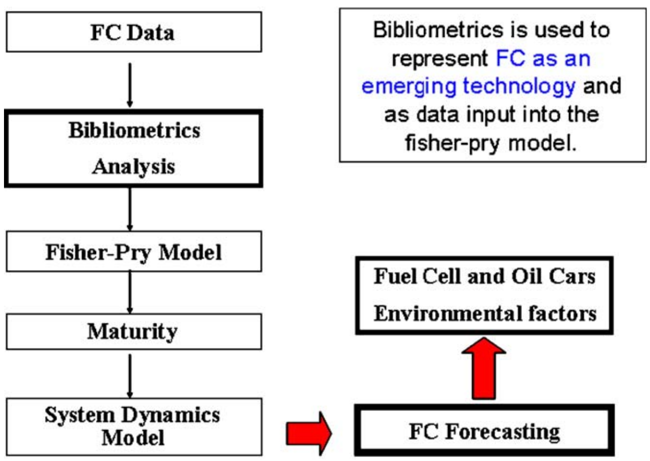


Fig. 4. Fuel cell model structure.

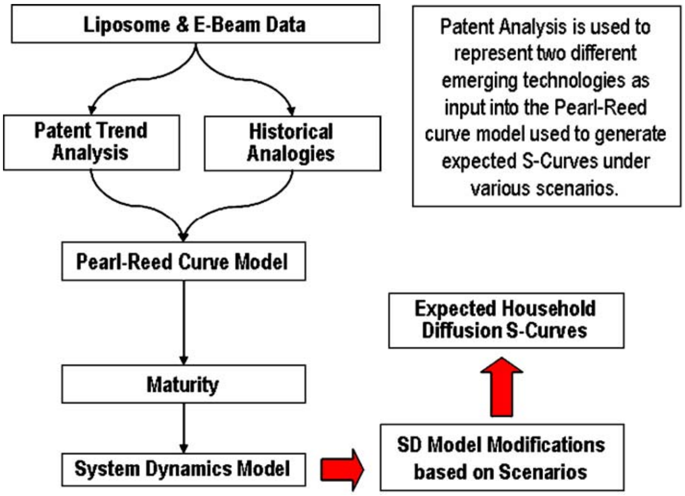


Fig. 5. Food safety model structure.

fuel cell case, historical data from the bibliometrics analysis and the Fisher–Pry model is used. However as Martino [36] described the upper limit should not be inferred from historical data. Then, we used expert data from the California Energy Commission (CEC) study [37]. Then, the Fisher–Pry results were incorporated into the SD model keeping in mind that the commercialization stage is going to start as soon as the development stage is finished. The way to make this functional in the model is making a right displacement of the S-curve assuming that adoption will have the same rate with development (Please see Fig. 4).

In the food safety application, patent trend analysis is used as an input to a Pearl–Reed curve model. Maturity levels are set using expert opinion. It is recognized that patents may represent the technological developments in an area but this needs to be married to the simulation of market needs in order to truly assess the future of any technology [15,10]. These market needs are modeled using various reinforcing

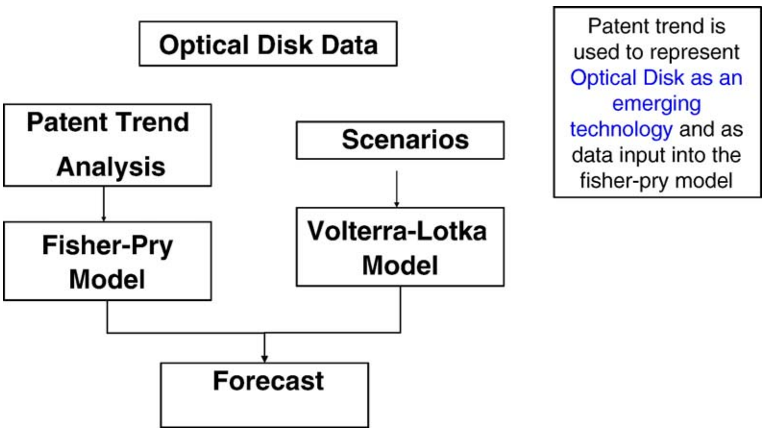


Fig. 6. Optical storage model structure.

and balancing feedback loops in an SD model. Scenarios are then defined based on expert and literature review and model variables are modified to simulate each possible scenario. A series of S-curves is generated that represents market penetration patterns under future conditions that can be used for decision-making and forecasting.

Optical disk application is structured in two parts; the first part analyzes the number of patents to determine the growth and substitution pattern of each storage technology and the second part applies the number of unit sales along with the assumption of some initial values of two different technologies at a time into the Volterra–Lotka competitive model to determine the competition and succession pattern of one over another. The analogy analysis approach is also applied to justify the assumption values based on various possible scenarios.

3.1. Application 1: Fuel cell technology in the U.S. automotive industry

Information from the Energy Information Administration (EIA), April 2004 [38], points out that the United States of America is the world's largest energy producer, consumer, and net importer ranking eleventh worldwide in reserves of oil, sixth in natural gas, and first in coal. Government reports have shown how energy demand has continued growing rates since 1970s. However, non-renewable energy resources are worth and limited. Then, efforts to reduce energy consumption levels and/or generate more energy alternatives to alleviate the current situation must be a constant effort that should motivate academics, scientists, managers and politicians at this time.

Rueda et al. [39] emphasized three forces pushing people to find energy alternative sources: i) energy demand is growing; ii) limitation of the fossil fuel reserves; and iii) environmental problems, emissions, generated by current sources. Fig. 7 illustrates how each consideration is a problem in the US economy. Fig. 7 shows how energy consumption has been increasing during the last 30 years and how after the 50s energy consumption has been always higher than production. For instance, in 2003 the net import accounted for 27% of all consumed energy [40].

Normally oil represents a big slice from the energy demand. For instance in 2003 petroleum accounted for 40% of the energy demand. Also, in 2003, petroleum accounted for 67% of the fuel consumed by the U.S. transportation sector. Fig. 8 shows how petroleum after the 1950s has increased its relative importance followed by coal and natural gas. Also, lately some forecasting models developed by EIA [40] showed petroleum resources going into frightening levels of consumption as described in Fig. 9.

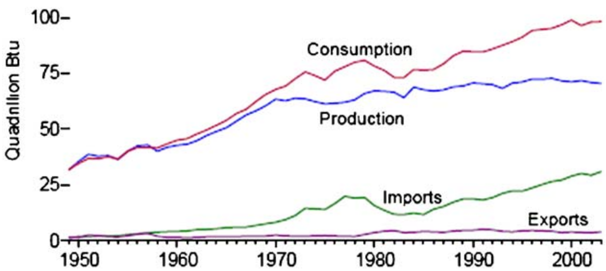


Fig. 7. Energy overview. Source: Annual Energy Review — Energy Information Administration, 2003.

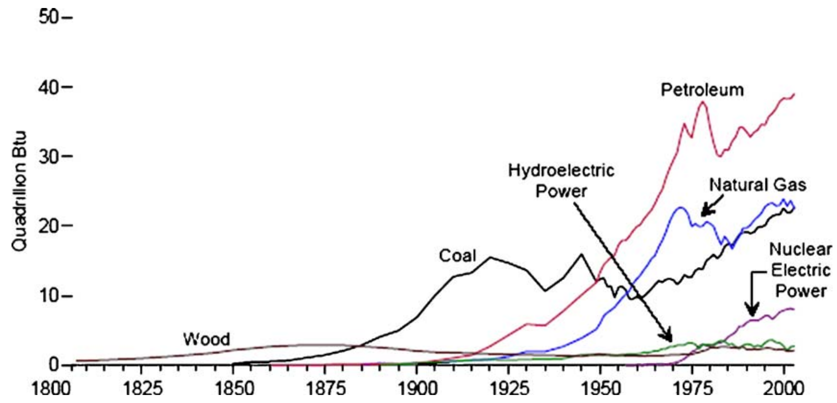


Fig. 8. Energy consumption by source. Source: Annual Energy Review — Energy Information Administration, 2003.

Third and lately considered as one of the most important factors will be the reduction of contamination levels to guarantee safe environments. Fig. 10 shows how CO_2 has been increased as a result of coal, natural gas and oil consumption.

Then the idea to find energy alternatives must be a constant goal in looking for different alternatives that can satisfy multiple perspectives: technical, organizational and personal [3] Several studies [41–43] has selected fuel cell as one of the most promising energy alternatives. Indeed, the US government has made public its support to FC as an energy alternative. In January 2002, Secretary of Energy Spencer Abraham announced the $1.2 billion FreedomCAR (Cooperative Automotive Research) program to fund research into hydrogen fuel cells for cars. It is a 10-year program intended to reduce vehicle emissions of greenhouse gases and other pollutants and to end the United States' dependence on petroleum.

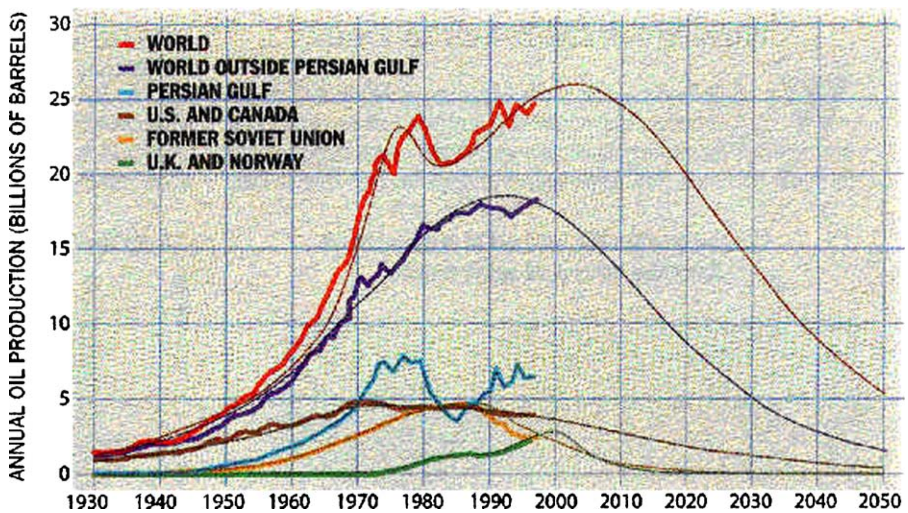


Fig. 9. Annual oil production. Source: Annual Energy Review — Energy Information Administration, 2003.

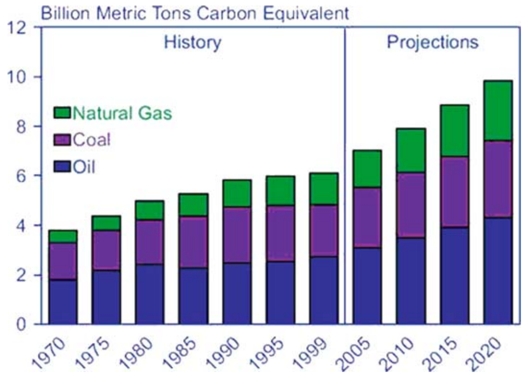


Fig. 10. World carbon dioxide emissions by fossil fuel, 1970–2020. Source: Energy Information Administration.

Then, two research questions blow up in order to prepare governments, organizations and people for the best future using fuel cell as energy alternative in the US industry:

RQ1. What will be the most likely future for the fuel cell technology in the automotive industry?
RQ2. How are the factors interrelated (structure) and which of the factors have the most influence over FC adoption rate (high-leverage)?

Considering that transportation consumption constitutes two-thirds of oil consumption [40] as described in Fig. 11. Then, the focus of the first case is going to be fuel cell in the US automotive industry.

For this study bibliometric is intended to be used in an exploratory phase as a proxy indicator for technology diffusion. Diffusion rate is obtained by the movement of bibliometrics S-curve from development to commercialization stage.

Martino [44] presents bibliometric analysis dividing the data in five categories as described in Table 3.

Once results have been obtained by author, organizations, countries and so on. Then bibliometric methods can be used to determine the technology life cycle position [44]. A typical pattern might be that "hits" in basic research would rise to a peak, then decrease as the "hits" on applied research began to increase and so on for the next cycles as presented in Fig. 12.

The data used in the bibliometric studies for the first case study come from the Science Citation Index and Business Elite Index. A previous bibliometric study in the FC area was developed by Porter et al.

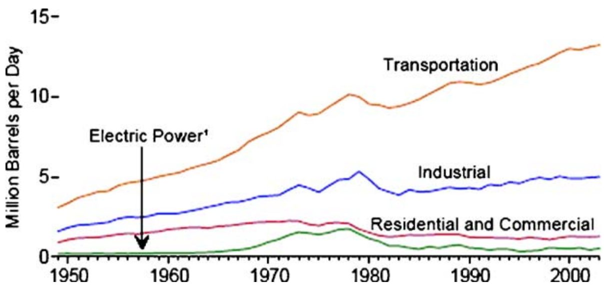


Fig. 11. Petroleum consumption by sector. Source: Annual Energy Review — Energy Information Administration, 2003.

Table 3
Sources for life cycle data [44]

R and D stage	Typical source
Basic research	Science Citation Index
Applied research	Engineering Index
Development	US Patents
Application	Newspaper Abstracts Daily
Social impacts	Business and Popular Press

[45,46] and results compared to this study are very similar until year 1998. Fig. 13 depicts the fuel cell (FC) number of publications since 1990s considering the Science Citation Index and Business Elite Index as data source. Then, it is clearly described by an S-shaped curve. However, the big problem will be to determine the inflection point and asymptote.

Then, the bibliometric data will be adjusted using an S-shaped curve as a way to fit the technological growth process [7] (pp. 175). The data was adjusted using a Fisher–Pry model as described in Fig. 14.

The upper limit or maturity point was defined using secondary sources of information from the California Energy Commission (CEC) [37]. In this case, we estimate 2010 as the year in which FC technology is going to be mature. Experts from the Delphi panel participating in the CEC study [37] considered unlikely that commercial fuel cell vehicles will be developed before this time. Also, reports from different automakers[1] make this assumption reliable. Some excerpts from BMW, DaimlerChrysler, Ford, GM, Toyota and Mazda are presented below. For the purposes of the model an initial market penetration of 10% is considered and increasing values will be added as soon as external factors will push technology acceptance. The CEC study also presented that FC market share is not expected to rise above 1% until 2010, and above 10% would not be likely before 2020.

Other methods may be to calculate maturity levels as a function of critical variables. For instance Porter et al. [7] proposed an index relation between the number of articles published in journals divide by the number of articles presented in conferences. Then, a higher frequency in conferences means that technology is in the initial stages wherein researchers are still looking for a peer-to-peer debate. Fig. 15 presents the relation between FC journals and conferences using the Compendex database.

Fig. 16 presents the general model developed to forecast the FC diffusion rate. Basically the number of cars is generated as a function of the US population. Positive, negative or neutral economies are considered to generate different scenarios.

Also, there are external forces, pushing and pulling, affecting the FC model. Some examples are represented by government policies, environmental or the index from oil consumption versus production affecting the FC diffusion. Also, additional variables are inserted into the models such as time to market, management responsive time and bibliometrics.

[1] BMW: "… the fist commercial sales of its hydrogen vehicles will occur before 2010, with 25% market penetration sometime after 2020…". DaimlerChrysler: "…The second phase step, called "fit for daily use," is expected to cover 2004 through 2007. The third segment is ramp-up and the fourth, starting about 2010, is full commercialization…". Ford: "… vehicles available for mass public consumption are projected to be available by 2010…" GM: "GM plans to establish high-volume FC production before 2010…". Toyota: "…Toyota is now much more guarded, asserting FC vehicles will not be commercial before 2010...". Mazda: "… announced ambitious plans to commercialize its hydrogen vehicle, with a target date of 2007 for production…".

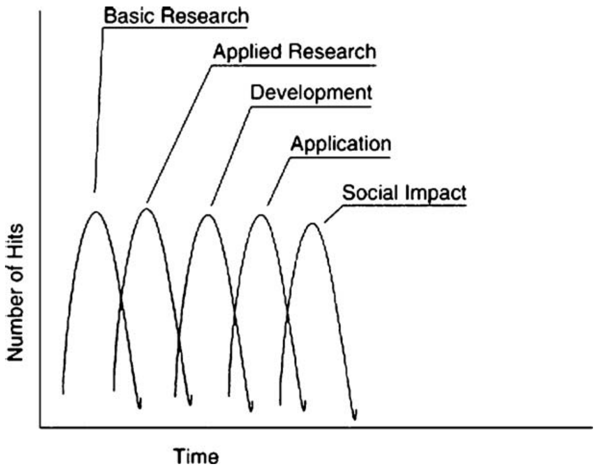


Fig. 12. Bibliometric estimate of stage of innovation [44].

The model was presented using the Stella software and for the FC model there are four sub-systems: population submodel, automotive submodel, environmental submodel and maturity submodel.

From the model we can summarize the following statements from each sub-system:

3.1.1. Population submodel

Basically the population submodel assumes that US cars are function of the US population. As mentioned before we run the model under different economy scenarios considering that number of cars are proportionally direct to the economy.

In general number of US cars is a function of population, the age, the average passengers by car and the percentage of historical people driven (See Fig. 17).

US cars = *f*(population, population age, driven market percentage, average passengers by car).

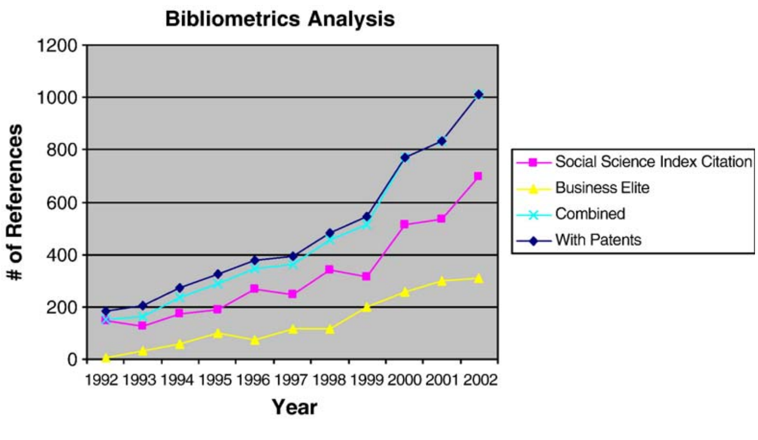


Fig. 13. Fuel cell bibliometric study. Databases used: Science Citation Index and Business Elite Index.

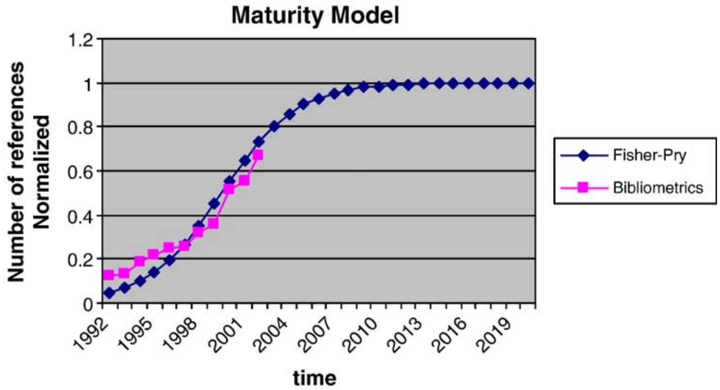


Fig. 14. Bibliometric data adjusted to the Fisher–Pry model.

3.1.2. Automotive submodel

The number of FC cars is a function of government policies, time to market, management response time, push to FC from gasoline consumption and production and maturity levels from bibliometrics (See Fig. 18).

FC cars = *f*(government policies, time to market (TTM), management response time (MRT), push to FC from gasoline and bibliometrics).

3.1.3. Environmental submodel

This sub-system computes the CO_2 emissions caused by the automotive industry. The analysis used parts per million (ppm) as measure is proportional to the number of cars. CO_2 emissions are function of the number of cars, gasoline and fuel cell, and the emissions caused by each type (See Fig. 19).

CO_2 cars = *f*(number of gasoline cars and fuel cell cars, CO_2 ppm by car).

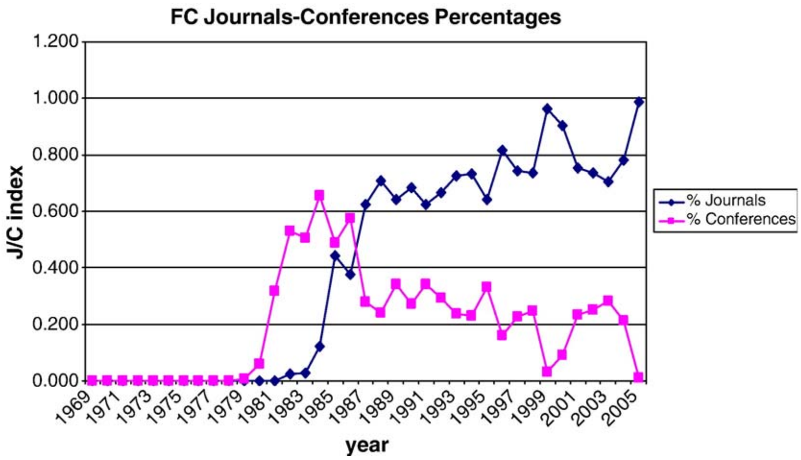


Fig. 15. Conferences versus journals production FC references.

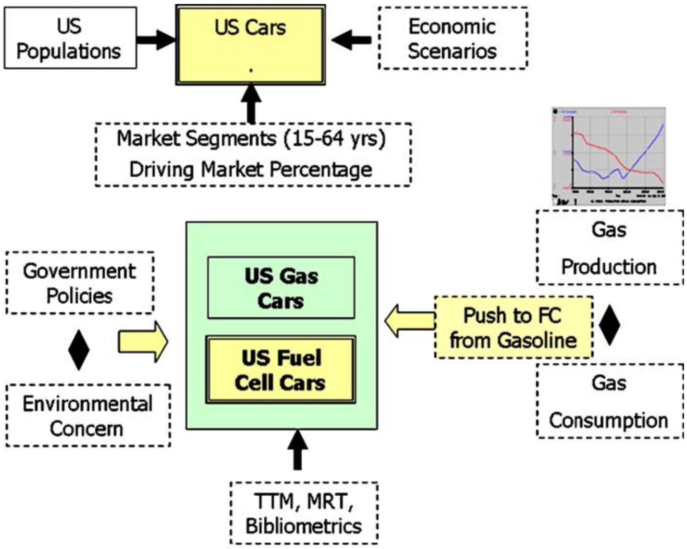


Fig. 16. Model structure.

3.1.4. Maturity submodel

Maturity level is defined as a single function from bibliometric analysis. In other words technology maturity is going to push FC market diffusion rate. As Martino [44] described a typical pattern might be that "hits" in basic research would rise to a peak, then decrease as the "hits" on applied research began to increase and so on for the next cycles as presented in Fig. 12. However, after FC maturity level is reached then additional variables such as government policies and US population will lead FC diffusion rate (Fig. 20).

3.1.5. Fuel cell results

Fig. 21 presents the interface that was designed using the Stella software to give the user more flexibility and the ability to run multiple scenarios in a practical way, just using knobs and switches.

Running the model we can get some interesting results as follows:

- The model is generating the US population 'endogenously'. Results are in average in the range of 1% of the historical data. Fig. 22 presents the historical and forecast data. The historical data is from the U.S. Department of Transportation.[2] Also passenger cars are endogenously generated and presented in Fig. 23.
- Fuel cell (FC) cars are highly affected by government decisions. The FC is defined as a chicken–egg problem by Eisenmann and Willis [42] in which consumers will not buy FC cars until the government develops enough infrastructures. However, the government does not develop the infrastructure until a critical mass network has been reached. Fig. 24 shows how FC adoption rate increases drastically in the points when governments made important investments being both highly correlated.

[2] http://www.bts.gov/publications/national_transportation_statistics/2002/html/table_04_11.html.

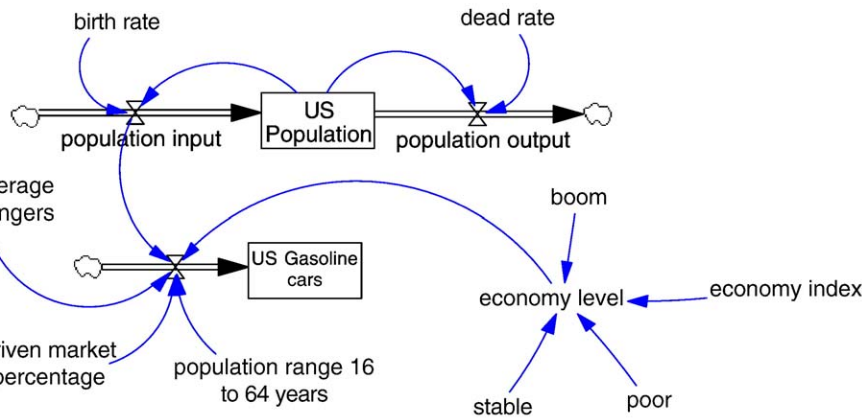


Fig. 17. Population submodel.

- Carbon dioxide emissions will continue increasing until FC will acquire big importance from the government and the people. At this point, the environmental effect will be noted. Fig. 25 shows the historical behavior and forecast results from the model. Results are generated endogenously being very precise compared to the real data.
- CO_2 effects will improve environmental conditions in the long-term. US Carbon Dioxide Emissions will be reduced in 7.6% and 3.6% respectively in 2004 and 2010 assuming 10% FC market share. However, today there are only testing models running in some U.S. cities (see Fig. 26).
- FC is highly dependent on two main variables: Bibliometrics that defined Maturity Level and the Index defined by the ratio between gasoline supply and demand. FC market share is growing as a consequence of maturity level until 2010 and later as a consequence of the gasoline supply/demand index determined by gasoline production and consumption levels (see Fig. 27).

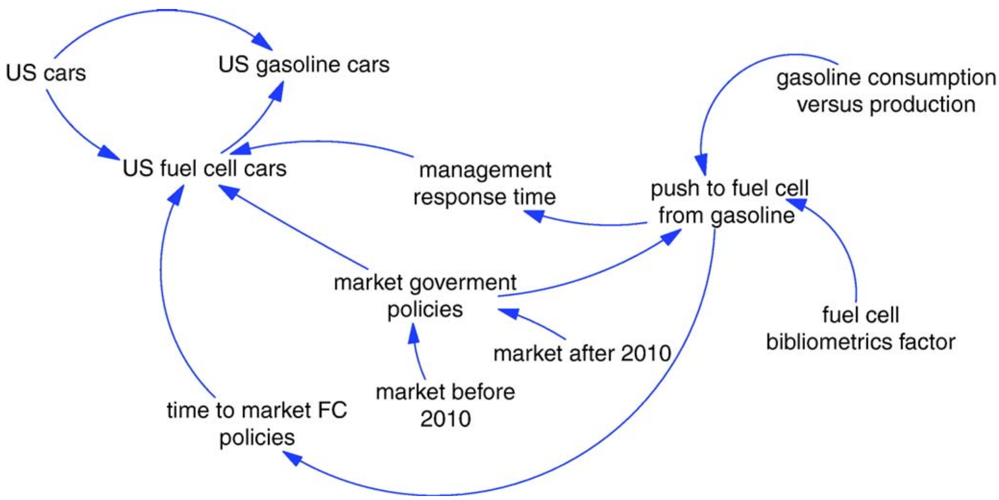


Fig. 18. Automobile submodel.

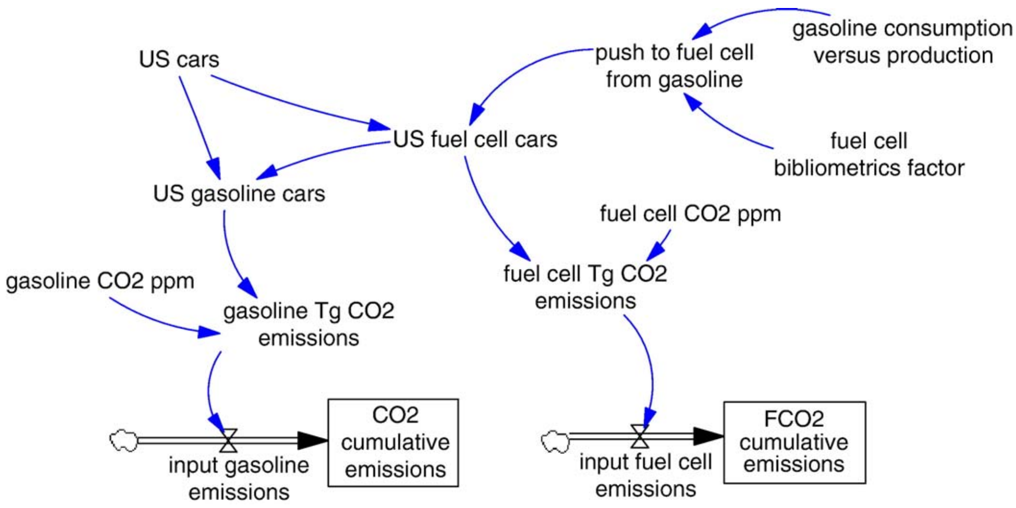


Fig. 19. Environmental submodel.

- Sensitivity is made following the Ceteris Paribus principle, emphasizing sensitivity in two main components: i) Government Policies and ii) Supply/Demand.

3.1.6. Fuel cell application discussion

As result of the simulation and running it over different scenarios we can conclude the following points:

- The trilogy government-automakers-and-people working together are indispensable for FC diffusion. None of these acting independently may leverage FC development.
- The FC market will increase adoption rate as a consequence of government policies and supply/demand relations.
- FC may not contribute significantly to the environmental issues in the first stage of their implementation. However, their environmental effects will be important in the long-term.

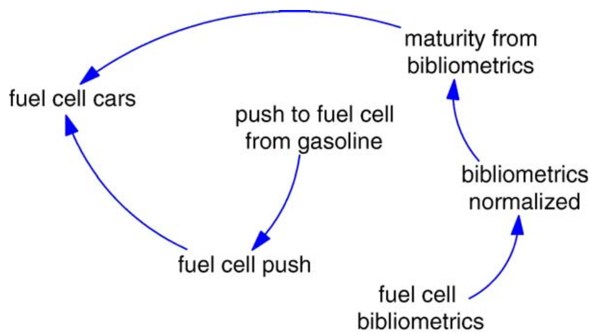


Fig. 20. Maturity submodel.

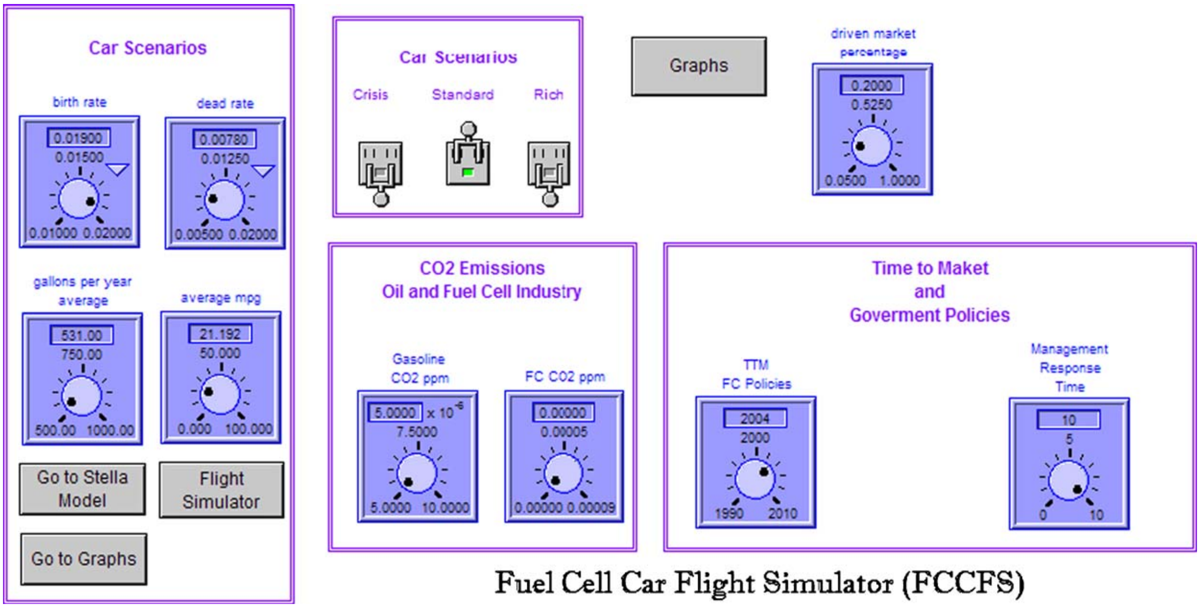


Fig. 21. Stella model interface.

- The proliferation of FC is highly dependent on achievement cost and performance levels. Then, reinforcing cycles will push FC adoption to high levels. However, serious FC challenges in terms of cost, performance and weight reductions still need to be overcome.
- The use of System Dynamics models makes the process very interesting, adding non-linear relations and feedback structures.

3.2. Application 2: Food safety technologies

The Center for Disease Control reports that each year at least 76 million people in the United States become sick from food borne pathogens [47]. Such illnesses result in 325,000 hospitalizations and over 5000 deaths annually. The medical costs and loss of productivity resulting from these illnesses range between $6.5 billion and $34.9 billion annually.

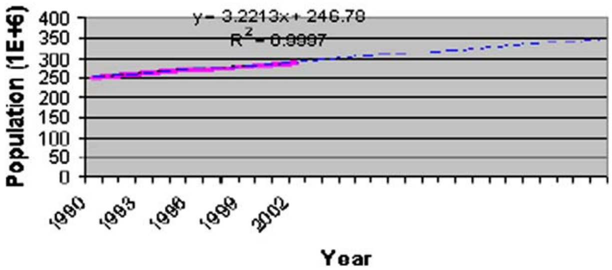
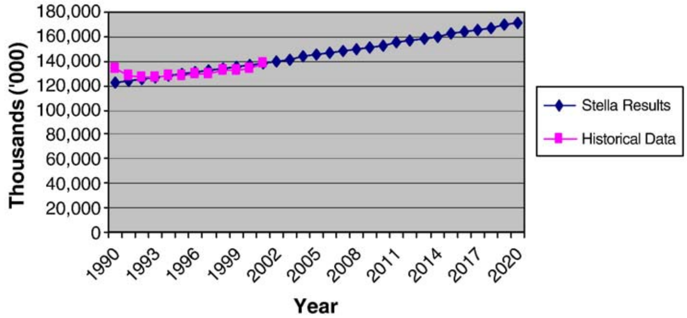


Fig. 22. U.S. population historical data.



Year	Vehicles Registered	Us Cars (Model)
1990	133,700	122,655
1991	128,300	124,028
1992	126,581	125,418
1993	127,327	126,822
1994	127,883	128,243
1995	128,387	129,679
1996	129,728	131,131
1997	129,749	132,600
1998	131,839	134,085
1999	132,432	135,587
2000	133,621	137,105
2001	137,633	138,641

Fig. 23. U.S. passenger cars.

There is currently no way for a consumer to determine if non-processed food that they've purchased is tainted or toxic. The safety of food and food products is a growing concern with recent identification of several bacterial and other microbial food borne pathogens. From a technological perspective, there are two major categories of food safety technology—testing technologies and elimination techniques. Fig. 28 shows these two technologies and the techniques related to each.

In an attempt to forecast the trend of two different food safety technologies, several external factors and similar technologies can be incorporated. Examples include cases of food borne illness or death, competing technologies, available medical technology, etc. All of these factors influence the potential commercialization of a new food safety technology. This research will use existing data of these external factors with trend analysis to provide insight to market reaction and commercial success under various scenarios.

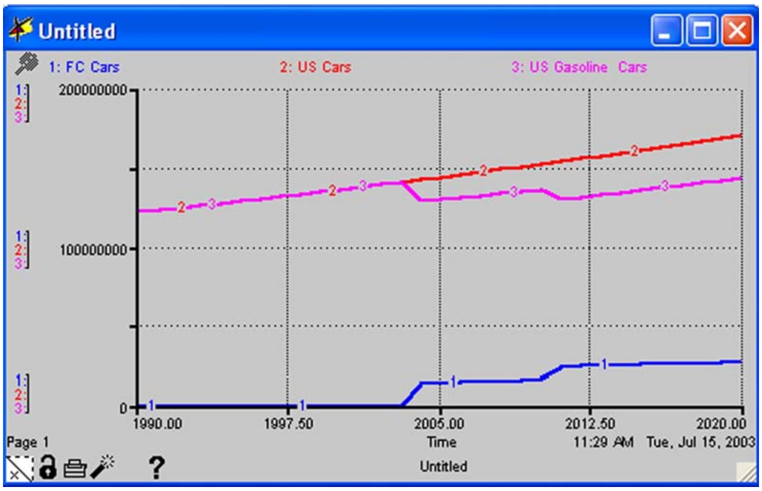


Fig. 24. U.S. automotive cars: oil and fuel cell.

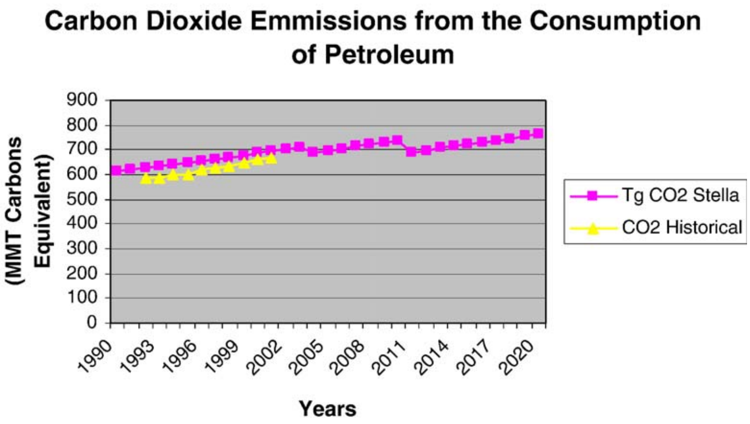


Fig. 25. Carbon dioxide emissions from oil and FC consumptions.

Two specific emerging techniques will be modeled—*liposome testing and electron (e-beam) elimination*. Patent trend searches reveal that both techniques are in the early stages of research for food safety application, with the potential for future household or industrial commercialization.

RQ1: For the most likely scenario of future food safety issues, what is the more promising technology for investment in future commercialization, elimination or testing techniques?

When modeling any complex system, several initial values and input parameters must be defined. The assumptions are summarized in the paragraphs below.

- Patent trend analysis. It provides information on technology trends in the development of new or improved products or processes. Since the two technologies in question are still in the development stages, patent analysis can be used to measure the research interest for each technology. The US Patent database is the source data for the second study. The cumulative number of U.S. patents for each technology is plotted over time. The patent rate is then fit to a logistic curve (Pearl–Reed Curve) as a

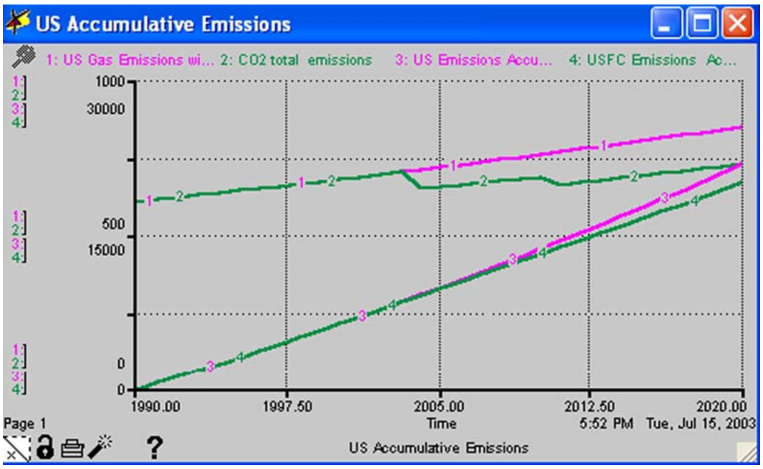


Fig. 26. CO_2 accumulative effects from FC.

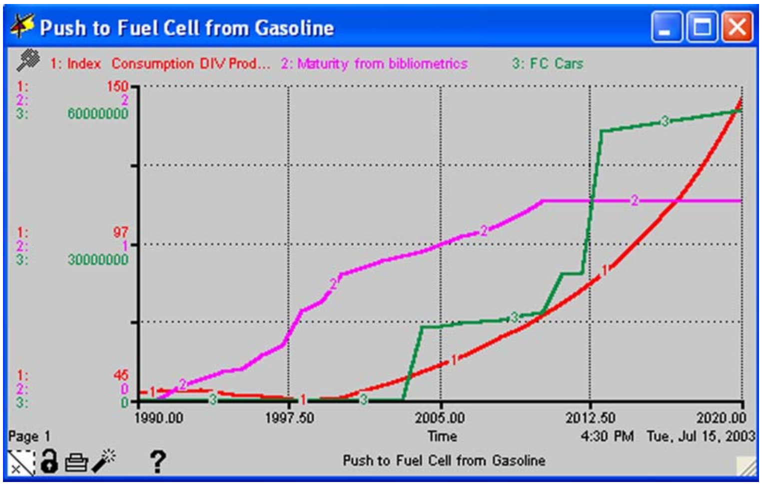


Fig. 27. Maturity and supply/demand index.

baseline rate of research for each specific technology. This equation is used to define the "research rate" as an input to the dynamic model. A control feedback loop is also used to define the horizontal asymptote of patents for the research rates. This number is best defined by expert panel with reflection of historical analogy to a similar mature commercialized technology (see Fig. 29).

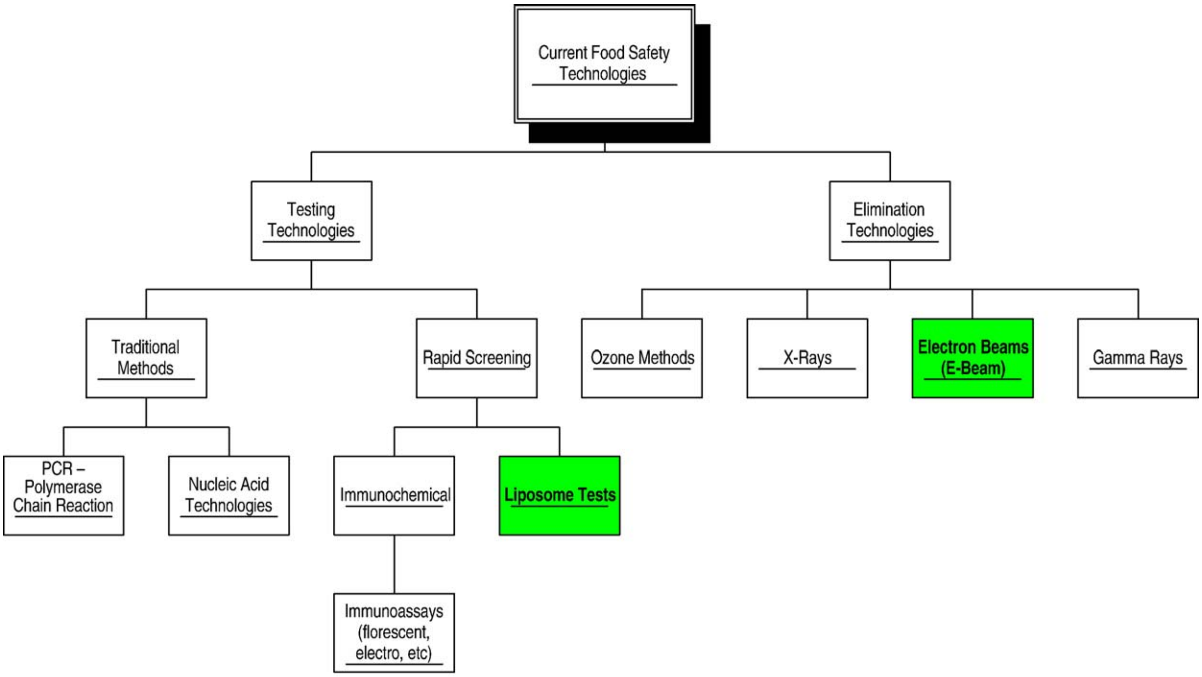


Fig. 28. Food safety technologies.

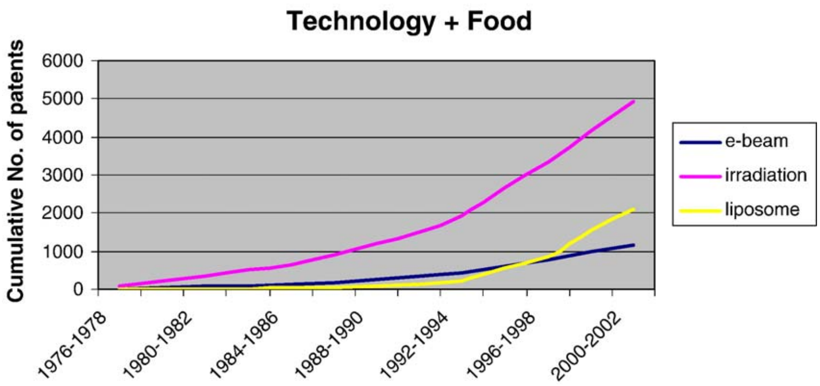


Fig. 29. Patent analysis rates by technology (www.uspto.org).

- S-Curves. They are used in the analysis of similar technologies to arrive at asymptote values for maximum market penetration. Similar technologies were selected in terms of function, target market, cost, risk, and availability. The model's S-Curve shape is generated by adding a control feedback loop that defines the maximum market penetration rate based on the historical analogy of similar household safety technologies.

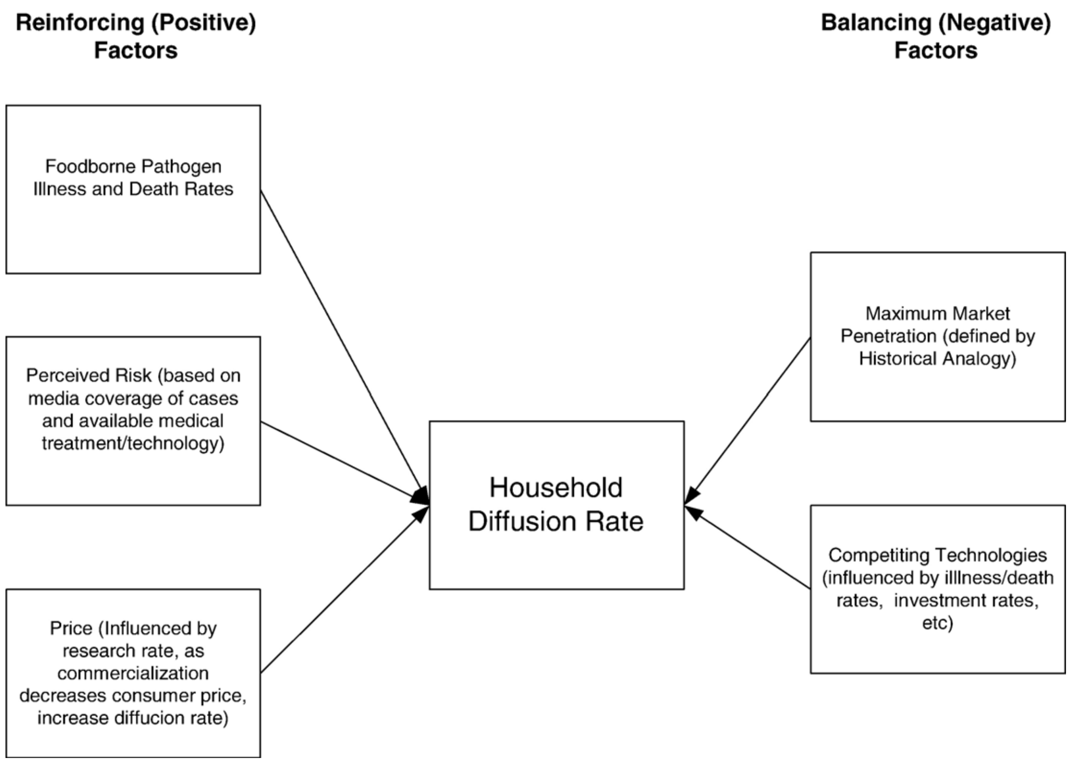


Fig. 30. Model structure.

▪ Scenarios. They are used by modifying initial input values and running the model to adjust possible government and public acceptance levels. Modification to initial values and projected growth rates enable multi-option analysis. Four scenarios were selected that adjust the input parameters similar to using a sensitivity-analysis to analyze potential growth rates. An expert panel should be used to define the scenarios and agree on the most likely.

The Systems Dynamic model created for this analysis is relatively simple and is based on the accuracy of the inputs and assumptions. Fig. 30 presents the basic structure of the model and the key variable of interest—the household diffusion rate. There are a number of positive (reinforcing) and negative (balancing) influences on this rate as defined by each variable. Each of these is a function of several external inputs such as public perceived risk level, available medical treatment, price, etc. The effect of the overall net feedback structure defines results over a projected 30 year span.

- Market Growth = *f*(Perceived Risk, Unit Price, Research Rate, Maturity Level)
- Perceived Risk = *f*(Food borne Illness Rate, Media Influence)
- Market Decline = *f*(Investment in other technologies, medical treatment risk)
- Investment Rate = *f*(Market Penetration).

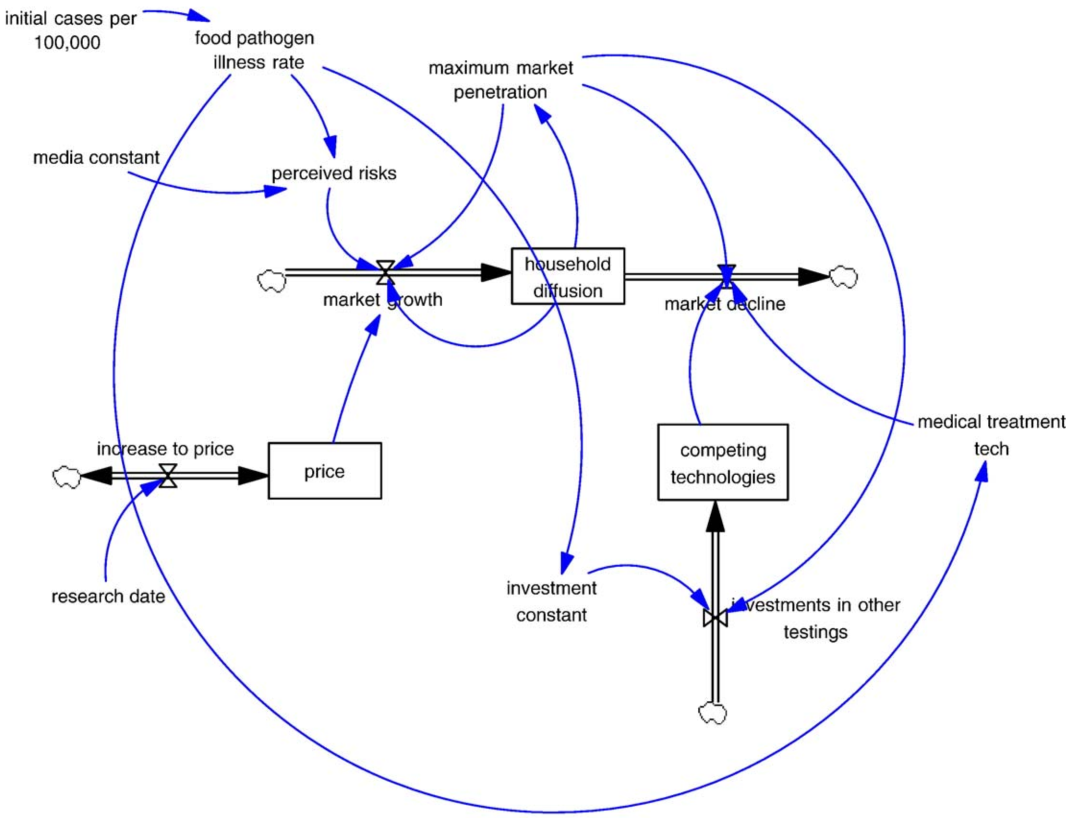


Fig. 31. Stella model structure.

Table 4
Four possible scenarios

Scenario	Government regulation	Number of illness/death cases	Media influence	Technology rate (patent rate)
Baseline	Average	Average	Average	Average
1	High	Decreasing	High	Reduced
2	High	Decreasing	Low	Reduced
3 most likely	Low	Increasing	High	Increased
4	Low	Increasing	Low	Reduced

Fig. 31 presents the structure of the model that was run for the four possible scenarios for each technology. The identical model structure was used for each technology in question with modified to the initial values and rates of change to represent the historical data for each. This gave a side-by-side comparison of projected household diffusion as a function of time to support potential investment decisions.

As initial results were summarized, verified and validated using sensitivity analysis and by comparing model output to historical analogies, the use of scenarios were incorporated based on possible influences from organizational variables (Table 4).

The output for each scenario was a group of S-Curves plotted over 30 years indicating the potential commercial success of developing each technology. The system ran each scenario over possible ranges for the variables in question as a type of sensitivity analysis. For certain scenarios, a commercial market was never identified due to a overbalancing of negative feedback such as the elimination of medical risk and an increase in the consumer price. The most likely scenario was selected based on literature reviews of trends for each exogenous variable.

Low government regulation of food industry: Neither the FDA nor the USDA regulate diagnostic products for industrial microbiology. AOAC, an independent organization oversees validation studies for

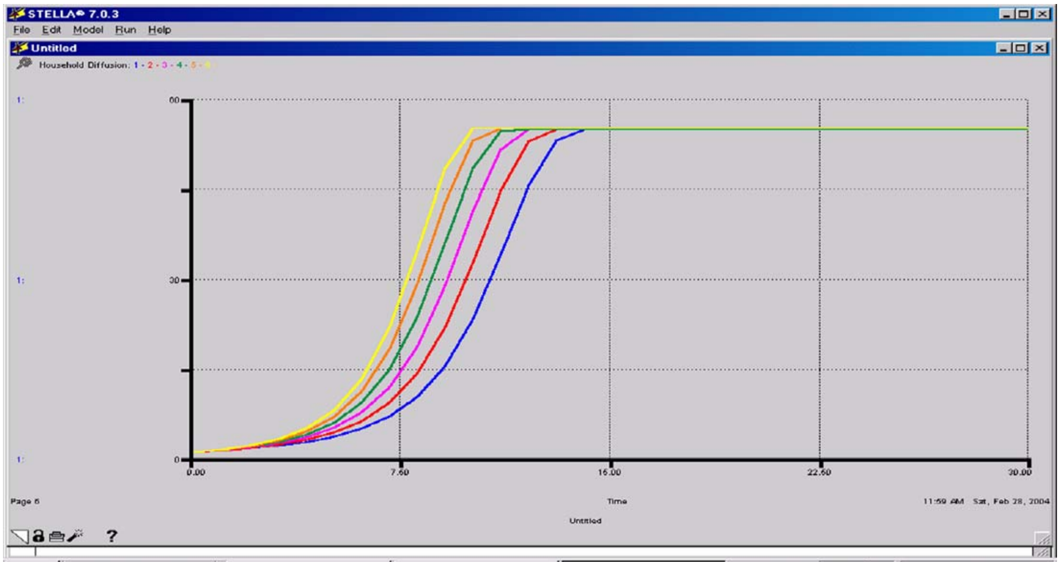


Fig. 32. Most likely scenario for liposome technology.

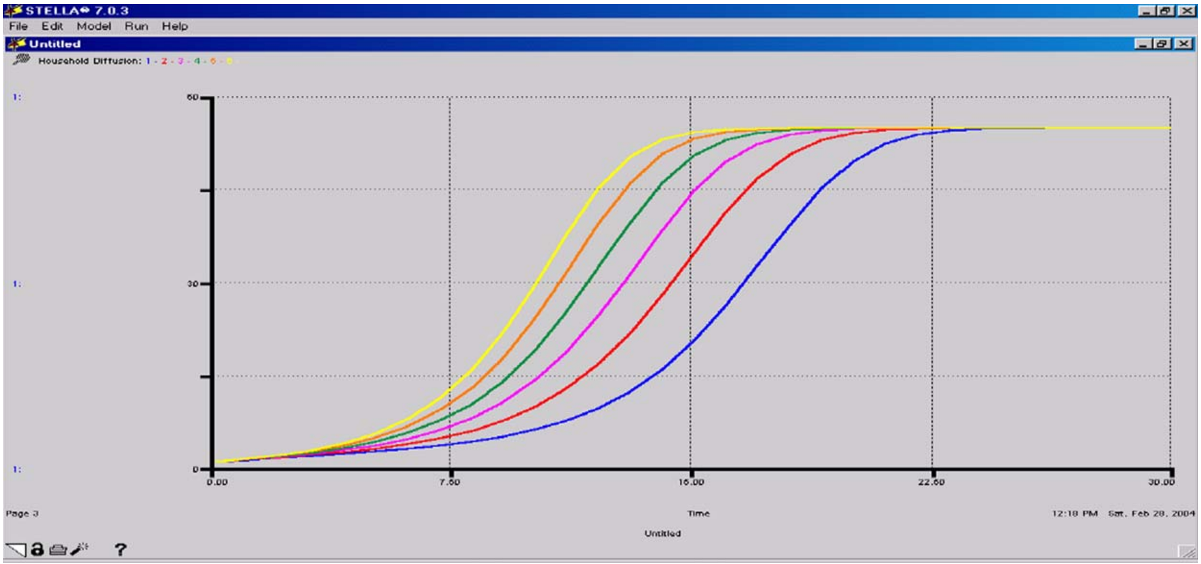


Fig. 33. Most likely scenario for E-beam technology.

new products. There is no evidence that the government plans to increase regulation in the industry any time soon [48].

Increase illness rate: CDC states "While technological advances such as pasteurization and proper canning have all but eliminated some diseases, new causes of food borne illness have been identified". Also, more and more cases go unreported due to lower percentage requiring formal medical attention [47].

High media constant: Public Perception is higher as the perceived risk increases with no new introduction of medical treatment technologies and an increase concern with media coverage.

Increase technology rate: Based on irradiation maturity analogy (a mature industrial food safety technology) and current growth it is highly unlikely that it would not reach at least this number.

The resulting graphs for both technologies are shown in Figs. 32 and 33. A sensitivity analysis has been plotted to show ± 5% variation on the research rate. Assuming no major breakthrough events, the market saturation for Liposome technology is about 5 years sooner than that for electron beams. This would suggest that investment in Liposome technology is a more promising venture for commercialization with earlier break-even timing, although for the most likely scenario both products show commercial promise given the similar market and social-health needs promoting the devices.

3.3. Application 3: Optical disk

In 1982, the first commercial optical storage device known as the Compact Disc (CD) was successfully introduced with the implementation of infrared technology [49]. Since then, the use of the Compact Disc had spread throughout industries. Until recently, the development of optical storage devices using red laser technology known as the Digital Versatile Disc (DVD) has been widely accepted by industries within a short introduction period. The sale of the DVD is expected to exceed that of the CD in 2003–4 [50].

Table 5
Physical characteristic of optical storage technologies

	Capacity per disc (GB)	Size of beam	Type of beam
Infrared	0.65	800	Wavelength laser
Red laser	4.7	650	Wavelength laser
Blu laser	23	405	Wavelength laser
Gallium ions	165	50	Ion (particle beam)

With an increasing demand for high capacity data storing especially for supporting new format of television contents, high density television (HDTV) [51], two research questions are proposed.

RQ1. What will be the future of optical storage technologies for electronic consumer products?
RQ2. What will be the estimated time for the substitution of the current technology (DVD) and expected emerging technologies?

To answer the first research question, literature search is conducted. The objective of this process is to search and assess potential candidates in optical storage technologies. From the literature search, the current development of optical storage technologies is defined.

It is found that the key players in the optical storage industry gather into two major consortiums led by Sony [52,53]. Their objective is to identify the new laser technologies which have smaller wavelength than red laser beam so that it could be compatibly functioned with High Density Television (HDTV). One of their discoveries is the blue laser technology [54,55]. At the same time, IBM and Norsam Corp. work together to develop the ion beam technology which is considered as one generation beyond optical laser [56]. The application of the ion beam technology is expected to be used in developing High Density Read Only Memory (HD-ROM). The physical characteristics of each technology are compared in Table 5.

To project the future development progress of various storage technologies by applying different technology forecasting methods including Patent Count Analysis, Fisher–Pry and Volterra–Lotka, two

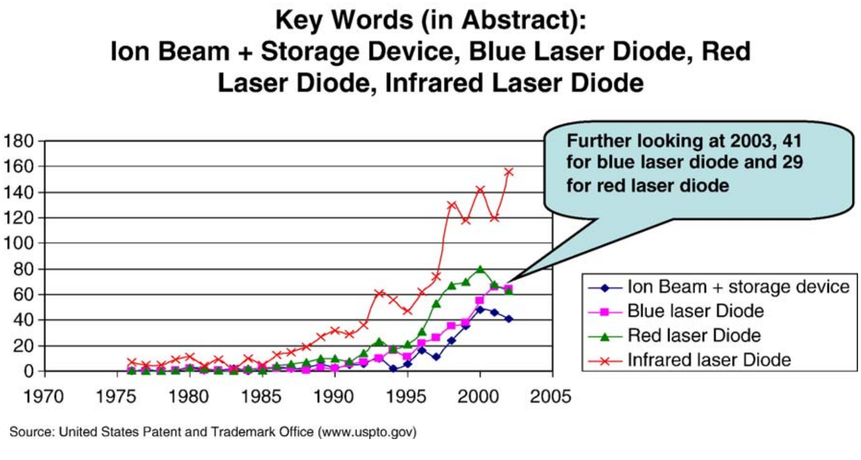


Fig. 34. The number of US patents by technology.

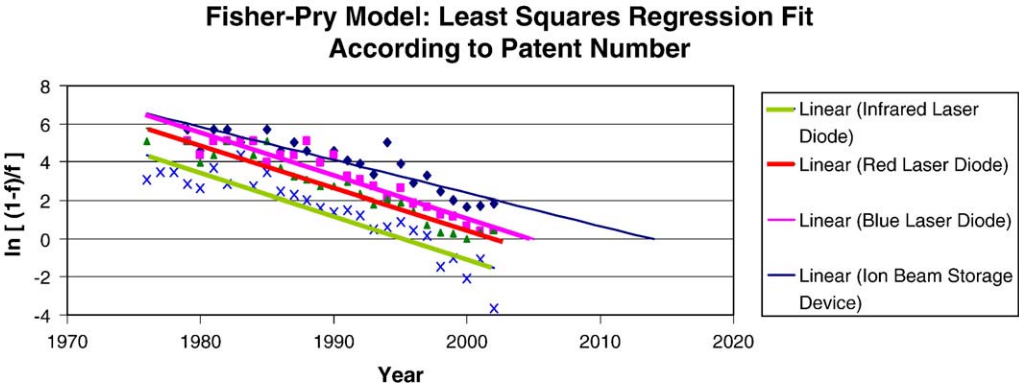


Fig. 35. Fisher–Pry model.

assumptions are defined after searching through various emerging optical storage technologies. First, with the continuous improvement of the amount of stored data, blue laser technology is likely to replace the use of red laser in consumer products. Second, the use of ion beam technology potentially breaks the glass ceiling of stored data capacity of traditional laser technology by replacing with ion beam technology.

4. Patent count analysis vs. Fisher–Pry growth model

To investigate the development activities of interested optical storage technologies, the number of patents of infrared laser, red laser, blue laser, and ion beam are obtained through the US patent database from 1976 to 2003. The number of US patents for each technology is plotted over time as presented in Fig. 34. From the obtained information, it is shown that the number of blue laser patents is about to exceed the number of red laser patents. In addition, the number of ion beam patents also surged over the past 5 years. These two observations do support the first assumption which defined above.

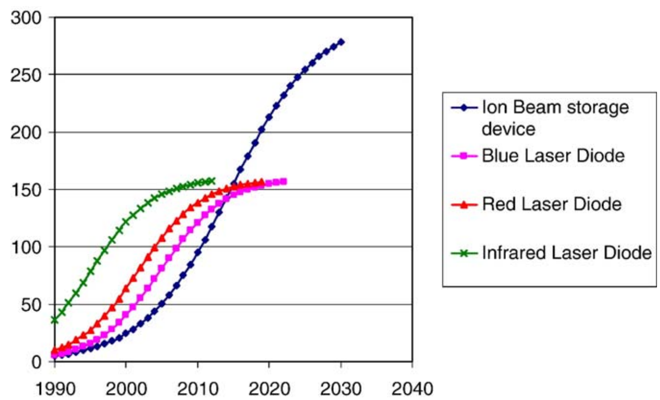


Fig. 36. Forecasting by using the Fisher–Pry model: the number of patents.

Table 6
Conditions based on scenarios

Initial conditions	Type of scenarios		
	Optimism	Neutral	Pessimism
Launched year	Blue laser: 2003 [51] ion beam: 2003	Blue laser: 2003 ion beam: 2005	Blue laser: 2003 ion beam: 2007
Initial population	Red laser: 23,760 K (II) blue laser: 960 K (III) ion beam: 50 K	Red laser: 23,760 K blue laser: 480 K (IV) ion beam: 35 K	Red laser: 23,760 K blue laser: 96 K (V) ion beam: 20 K
Market capacity	70 M [56]	30 M (VII)	25 M (VIII)
Competitive coefficients	Initial population divided by market capacity		
Growth rate	Red laser: 0.35 (IX) blue laser: 1.16 [57] ion beam: 1.16 (XI)	Red laser: 0.30 blue laser: 0.9 ion beam: 0.6 (XII)	Red laser: 0.25 blue laser: 0.6 ion beam: 0.4

(I). Launching year of blue laser product.
(II). 35% is the DVD growth rate from the unit sale growth from 2001 to 2002.
(III). 20% penetration in current 4.8 million households owned HDTV in the first year.
(IV). 10% penetration in the first year.
(V). 2% penetration in the first year.
(VI). Upper bound of unit sales in VCR, CD, and DVD players.
(VII). Upper bound of unit sales in VCR and DVD players.
(VIII). Upper bound of unit sales in VCR.
(IX). Unit sales growth from 2001 to 2002.
(X). Analogy from DVD player unit sales from 1997 to 2002.
(XI). Analogy from DVD player unit sales from 1997 to 2002.
(XII). Analogy from CD player unit sales from 1997 to 2002.

In depth analysis, the number of patents is used as an input for the determination of growth and substitution pattern of each storage technology by applying the Fisher–Pry growth model. To perform the process of growth model transformation, the upper growth limit (upper bound) for each technology

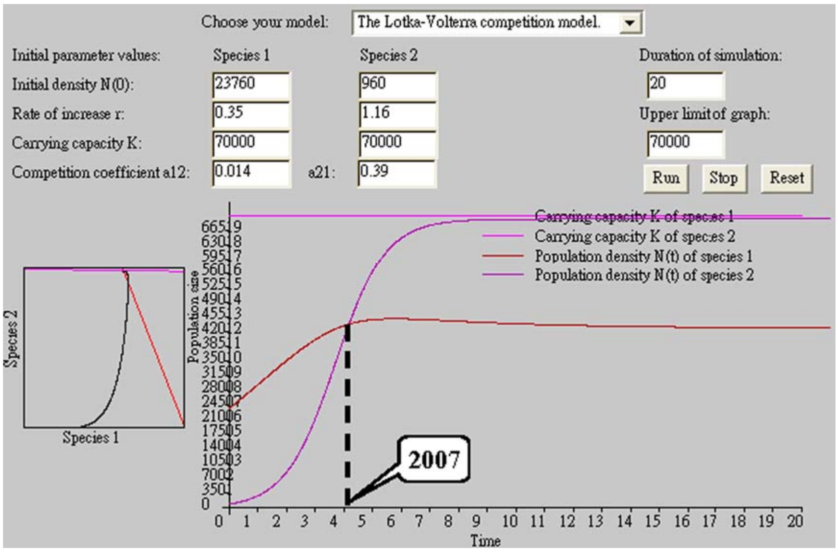


Fig. 37. The substitution of blue laser for red laser.

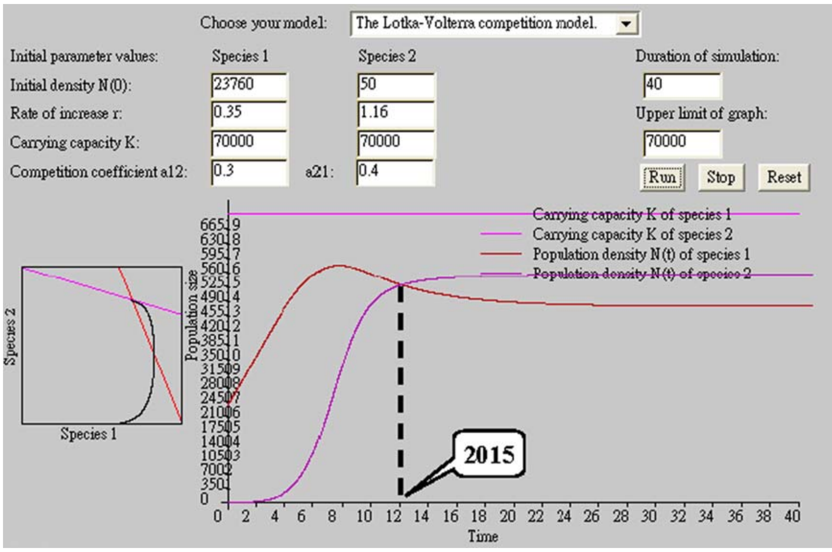


Fig. 38. The substitution of ion beam for blue laser.

is defined. In this case, the number of patents of infrared laser technology at 160 is defined as an upper growth limit for any wavelength laser technology, infrared laser, red laser, and blue laser. Another US patent search using the key word "optical diode" is performed to represent the upper growth limit for ion beam since this new way of storing data is expected to replace all wavelength laser technologies using typical optical diode. The results of applying the Fisher–Pry growth model are shown in Figs. 35 and 36.

From the Fisher–Pry growth model using the number of patents analysis, it can be interpreted that blue laser technology is likely to replace red laser technology in 2006–7, and ion beam is likely to replace blue laser technology in 2015.

4.1. Volterra–Lotka vs. scenarios analysis

In the second part of this case study, a forecasting methodology called the Volterra–Lotka competitive model as well as scenarios analysis is applied. The number of unit sales is obtained along with the

Table 7
The comparative result analysis

Scenario results	Unit sales analysis			Patent analysis (2–3 years ahead market)
	Optimism	Neutral	Pessimism	
Blue laser product launched year	2003	2003	2003	
Ion beam product launched year	2003	2005	2007	
Substitution of blue laser for red laser	2007	2009	2014	2006 (2008)
Substitution of Ion beam for blue laser	2015	2019	2021	2015 (2017)

assumption of some initial values of two different technologies at a time into the Volterra–Lotka competitive model to determine the competition and succession pattern of one over another.

In order to conduct the analysis comprehensively, all necessary initial conditions are defined according to three potential scenarios, optimism, neutral, and pessimism (Table 6).

After defining all initial conditions, the Volterra–Lotka competitive model is run in three scenarios. The examples of results under the optimism scenario are presented in Figs. 37 and 38. From Fig. 37, it is indicated that the unit sale of consumer product equipped with blue laser technology will catch up with consumer product equipped with red laser technology in year 2007. Furthermore, the results from Fig. 38 indicate that the unit sale of consumer product equipped with ion beam technology will catch up with consumer product equipped with blue laser technology in year 2015. A publicly available software was used for the analysis [58].

As presented in this case study, the forecasting of optical storage technologies are achieved through the analysis of two main types of data; number of patents and number of unit sales. Forecasting of technology can be done with the use of a combination of multiple technology forecasting methodologies, techniques, as well as assumptions. To summarize all findings of this case study, the comparative results analysis of the case study is presented in Table 7.

5. Conclusions and future work

This paper demonstrated that technology forecasting results can be improved by integrating multiple methodologies. The use of patent analysis and bibliometrics provide historical data missing in the case of emerging technologies.

This paper demonstrates the need for development of such integrated tools for technology forecasting. By using methodologies to represent the technical or data driven models and using scenario planning to anticipate organizational and personal behaviors, a more complete forecasting methodology is introduced.

For future work, several case studies are needed to validate bibliometrics as a proxy indicator for technology diffusion. Also, a Delphi process with experts would increase model reliability to measure technology diffusion.

Based on our results and literature we propose a table for methodology selection. We propose that methodologies for emerging technologies will vary from the existing technologies and that there are stages through which a forecasting project should go through. Data is based on our learnings from the applications presented in this paper. We also refer to Delphi process although we have not used it in our applications (Table 8).

Furthermore we are providing an outline of a phased technology forecasting framework which should lead to future research.

Table 8
Technology forecasting method selection table

Methodologies	
Data collection	Patent Analysis, Bibliometrics, Analogies, Delphi
Relationship building	Delphi, System Dynamics
Diffusion/forecasting	System Dynamics, Scenarios, Growth curves

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